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A Novel Supervised-Unsupervised Approach for Past-Due Prediction

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Abstract

In the current landscape of banking and financial services, a primary concern for industry practitioners revolves around predicting the probability of default (PD) and categorizing raw data into risk classes. This study addresses the challenge of predicting payment past-due for customers of Residential Mortgage-Based Securities (RMBS) and Small and Medium Enterprises (SMEs) within the Italian banking sector, employing an innovative approach that integrates a classification model (Random Forest) with an anomalies detection technique (Isolation Forest). The models are trained on a substantial dataset comprising performing loans from the 2020-2022 period. Notably, this research stands out not only for its novel modeling approach but also for its focus on the arrear status of RMBS and SME customers as the target variable. By concentrating on past-due rather than the broader concept of probability of default, this approach enhances understanding of customers' financial stress levels, enabling proactive monitoring and intervention by decision-makers. The ultimate aim of this experimentation is to develop a robust and effective algorithm applicable in real-world scenarios for predicting the likelihood of past-due among individual customers and companies, thereby supporting management decision-making processes. Empirical results demonstrate that the proposed framework surpasses conventional statistical and machine learning algorithms in credit risk modeling, exhibiting robust performance on new data (validated against 2023 data) and thus proving its operational suitability.

JEL Classification: G21, G24, G32

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1. Foreword

Credit risk modeling is a cornerstone of financial research and risk management, especially in the aftermath of financial crises. Accurate and comprehensive tools to assess credit risk are essential for mitigating potential losses and ensuring the stability of financial institutions. This section aims to provide a thorough review of the key methodological approaches used in the literature for modeling the probability of default (PD). It includes insights from both empirical applications and academic research, identifies existing literature on credit risk, and explores new empirical methodologies to underscore the novelty of the proposed model.

Traditional models often employ binary classifications to determine credit default, focusing on whether a borrower is over 90 days in past-dues. However, this approach can result in the loss of valuable information by reducing the continuous measure of days past due to a simple binary variable. The financial crisis of 2008-2009 particularly heightened interest in understanding the factors affecting credit access for small and medium-sized enterprises (SMEs), which are heavily dependent on direct lenders and were significantly impacted by reduced credit availability following banking shocks.

Historically, discrete choice methods have been used to model credit default. These models typically define a binary dependent variable based on a standardized definition of default, reducing continuous measures like days past due to binary outcomes. While this method is straightforward, it potentially overlooks valuable information that could enhance model accuracy and risk prediction.

Credit default indicators exhibit persistence over time, suggesting that using lagged days past due could improve default prediction by leveraging temporal information. This analysis focuses on two borrower categories: SMEs and household borrowers, both of which play crucial roles in the economy. SMEs, in particular, are vital for employment, income generation, and fostering innovation and growth.

For residential mortgages, credit risk assessment primarily focuses on the borrower's equity in the property as a key default determinant. Risk management in financial modeling has led to extensive experimentation with various algorithms to achieve optimal classification performance. This review covers traditional statistical models, machine learning techniques, and hybrid approaches, evaluating their effectiveness in predicting default probabilities.

The article follows a structured approach that begins with a comprehensive literature review, examining key methodological approaches in credit risk modeling. This review explores both empirical applications and academic perspectives, providing a foundation for understanding current practices and identifying gaps in existing literature. Subsequently, the article delves into detailed case studies, examining specific datasets and scenarios pertinent to credit risk assessment, particularly focusing on residential mortgage-backed securities (RMBS) and small and medium-sized enterprise (SME) loans. Following this empirical foundation, the article presents a robust methodological framework that integrates supervised and unsupervised learning techniques, aiming to enhance predictive accuracy in default probability modeling. Finally, the article concludes with insightful remarks, discussing the implications of the proposed model and suggesting avenues for future research and application in the field of credit risk management.

2. Literature Review

The objective of this section is to review the main methodological approaches available in the literature to model the probability of default, both in empirical applications and from an academic perspective. Furthermore, we aim to identify the existing literature on credit risk and explore new empirical methodologies. In doing so, we aim to highlight the novelty of the proposed model.

Credit risk modelling is a critical area of research in finance, particularly relevant in light of the financial crises, which have highlighted the need for more accurate and comprehensive risk assessment tools. Traditional models have typically used binary classifications to determine credit default, focusing mainly on whether a borrower is more than 90 days. However, these models can lose valuable information by simplifying days past due into a dichotomous variable. The financial crisis of 2008-2009 increased the interest of economists and regulators in understanding the factors affecting access to credit for small and medium-sized enterprises (SMEs). SMEs, which are highly dependent on direct lenders, are particularly affected by reductions in credit availability following banking shocks (Berger and Udell, 2002; Wehinger, 2014).

Credit default has historically been modelled using discrete choice methods, first proposed by Altman (1968) and later developed by others such as Löffler and Maurer (2011), Bonfim (2009) and Carling *et al*. (2007). These models typically define a binary dependent variable based on the Basel Committee on Banking Supervision's (BCBS, 2006) definition of default, which considers a borrower to be in default if he or she is more than 90 days in past-dues. Although effective, this approach reduces a continuous measure (days past due) to a binary outcome, thereby losing potentially useful information that could improve model accuracy and risk prediction.
Credit default indicators are known to be persistent over time. Once a borrower has defaulted, the likelihood of a quick return to compliance is low. Similarly, once the number of days in default becomes positive, it tends to remain so, showing positive serial correlation. This persistence suggests that the use of the number of lagged days could improve the prediction of future defaults by exploiting this temporal information, an advantage that standard default prediction models typically do not exploit.
This analysis is conducted for two categories of borrowers: SMEs and household borrowers.
SMEs play a crucial role in the economy, generating employment and income and fostering innovation and growth. In the euro area, SMEs account for around 99% of all enterprises, employ around two-thirds of the labour force and contribute around 60% of value added (Gagliardi-Main *et al*., 2013). The economic importance of SMEs is particularly pronounced in southern European countries such as Italy, Spain and Portugal. During the financial crisis, SMEs experienced a double shock: a significant reduction in demand for goods and services combined with tighter credit conditions, which severely affected their cash flows.
The sovereign debt crisis of 2011 further exacerbated these challenges, particularly for Italian banks (Bofondi, Carpinelli and Sette, 2013). SMEs generally face higher credit risk than large firms due to greater information asymmetries. Banks often have limited access to detailed financial information on SMEs, making it difficult to accurately assess their creditworthiness (Berger and Udell, 1995; Degryse and Van Cayseele, 2000). This information gap leads to higher perceived risk and may result in tighter credit conditions for SMEs (Ivashina, 2009). SMEs generally have less stringent accounting requirements and fewer incentives to invest in detailed disclosure practices (Baas and Schrooten, 2006), contributing to banks' reluctance to lend.
Credit risk assessment for residential mortgages focuses mainly on the borrower's equity in the property as a key factor in the default decision. If the market value of the house exceeds the value of the mortgage, the borrower has a financial incentive to sell the property rather than default. Option-based theories view mortgage default as a put option, where the borrower can transfer the property to the lender to pay off the debt. Borrowers exercise this option when the market value of the house falls significantly below the value of the mortgage, although high transaction costs and reputational damage reduce the likelihood of a 'merciless' default. Equity-related factors influencing default rates include the initial loan-to-value ratio, house price appreciation rates, mortgage seniority, mortgage term and current interest rates. A mortgage interest rate below current market levels discourages default, as a new mortgage would have a higher interest rate.

Risk management has always been a primary concern in financial modeling, prompting extensive experimentation with various algorithms and techniques to achieve optimal classification performance. In this section, we will provide detailed evidence of the different methodologies employed historically and contemporarily in credit risk modeling. This review will cover traditional statistical models, machine learning techniques, and hybrid approaches, evaluating their effectiveness in predicting default probabilities.

At a broad level, the probability of default (PD) problem can be framed as the development of an algorithm or methodology to predict a target variable (Y), typically encoded as a binary variable (0/1), where a value of 1 indicates the occurrence of a default event and 0 otherwise. A diverse range of variables can be utilized to predict the probability of default, encompassing both intrinsic characteristics of the borrower, such as demographics in the context of business-to-consumer (B2C) lending or industry and firm size in business-to-business (B2B) applications, and financial indicators and key performance indicators (KPIs) related to the financial behavior of the subjects under study.

Variables commonly employed as independent predictors in credit risk measurement can be categorized into quantitative variables (based on financial ratios), behavioral variables, and qualitative or "soft" factors (Gabbi, Matthias and Giammarino, 2019). Among the most frequently used models in credit risk management, quantitative variables derived from historical balance sheet data and trends are predominant for both loans and bonds (Gabbi & Sironi, 2005). Due to the historical nature of many of these data, they can often induce procyclicality effects (Gabbi & Vozzella, 2013). Regulatory authorities have acknowledged that the Basel II framework contributed to undesirable effects on system stability during financial crises, resulting in credit crunch phenomena that particularly affected small and medium-sized enterprises (SMEs) whose access to credit may be influenced by regulation (Gabbi & Vozzella, 2020).

There is compelling research highlighting the efficacy of qualitative variables in approximating future business dynamics, management plans, and company perspectives (Brunner *et al*., 2000; Morales *et al*., 2000; Grunert *et al*., 2005). Several studies (Lehmann, 2003; Grunert, Norden, & Weber, 2005; Godbillon-Camus & Godlewski, 2005) have identified the opacity of information processed by banks as a significant challenge in assessing the credit risk of loans to SMEs. The utilization of forward-looking information enables SMEs to mitigate information asymmetries relative to larger companies and reduces the risk of credit crunch (Grunert & Norden, 2012; Howorth & Moro, 2012). While regulation for internal models does not mandate specific variables, it encourages banks to diversify their input sources to adequately capture the complexity of credit risk (Basel Committee on Banking Supervision).

Several systematic literature review publications on banking probability default methodologies are available, Dastile *et al* (2020) and Alaka *et al* (2016), Brown and Mues (2012), all pointing out in the direction of two main class of techniques developed and applied to default prediction, namely statistical techniques and Machine Learning and Artificial Intelligence based techniques.

With reference to classical statistical technique, most of the relevant publications implementes logistic regression modeling like in Steenackers and Goovaert (1989), Arminger *et al* (1997) and West (2000) or alternatively linear and quadratic discrminant analysis as in Desai *et al* (1996), West (2000) and Baesens *et al* (2003). Regarding the main results, these techniques proved to be quite good at predicting the investigated phenomenon, providing - above all - interpretable results on the variables that most influence the outcome. However, in cases of dataset where the relationship between predictors and the target variable follows non linearities, interaction and complex effects these methods are not well-suited, unless the functional form of the relationships is known or discovered *ex-ante*.

Alternatively, Machine Learning based techniques has been experimented for the same purpose with a very good level of performance. More specifically, tree-based methods and Artifical Neural Networks have been found wide applications in this domain. With respect to tree-based methodologies, Classification Trees has been tested like in Arminger *et al* (1997), Yobas *et al* (2000) and more recently in Feldman and Gross (2005) for mortgage default prediction. In addition, ensemble methods such as Random Forest algorithm (Brieman, 2001) as well as Gradient Boosting Methods (Friedman, 2001 and Friedman, 2002) have been implemented proving to obtain relevant results in this domain of application like in Zhu *et al* (2019) and Ma *et al* (2019). In addition, neural networks architectures have been also widely applied for loan default predictions both as experimental methodologies like in Angelini *et al* (2008) and Khashman (2010) as well as in comparative algorithm performance studies like in Petropoulos *et al* (2019). However, despite being very performative in practice, the implementation of these algorithms comes with limited or none interpretability of the results, making extremely challenging to understand which are the financial ratios, KPIs and demographics that could potentially most influence the probability of default. To address this problem, not only circumscribed to this kind of applications, several tools of explainable AI have been developed in recent years, among which the most used are Variable Importance (Fisher *et al*, 2019), Partial Dependence Plot (Friedman, 2001) and SHAP (Shapley value) plot as described in Song *et al* (2016) and Frye *et al* (2020). Several examples of application of explainable AI tools are available in this regard: Brake *et al* (2019) showed how explainable machine learning could be used in the finance sector, whereas Bussmann *et al* (2021) provide evidence on how these techniques could be potentially applied to credit risk management, focusing on SHAP value and variable importance. Besides this supervised approach, it is worth noting that some applications are trying to leverage on unsupervised learning methodologies as well, like implementing Isolation forests (Liu, 2008) for credit card transactions has been addressed by Ounacer *et al* (2018).

It is relevant to note that the previous literature review is not exhaustive of the vast domain of application under investigation, but this section of the work has been organized bringing in the most relevant academic references for the followed methodological approach.

3. Case

This study focuses on developing an algorithm to predict loan arrears within two segments of the portfolio: Residential Mortgage-Backed Securities (RMBS) and Small and Medium Enterprises (SMEs). Unlike traditional credit risk models that predominantly emphasize borrower default, this research innovatively centers on forecasting loan arrears, which serves as an early indicator of potential defaults. Specifically, this section aims to achieve two primary objectives:

- Providing an overview of the dataset utilized in the algorithm's application and implementation;
- Detailing the dataset restructuring process undertaken for analysis and outlining the classification of various Key Performance Indicators (KPIs) computed for this purpose.

3.1 Data

The data used in the current analysis are coming from a wide database of loans of different banks. The banks that provided data can be considered medium to small in the context in which they operate. From a geographical point of view, the banks in the sample are spread all over the Italian territory. The data were provided in anonymised form by a private company that manages certain information on behalf of these banks. As described above, RMBS and SME data has been analyzed: in particular, roughly 4 million of cases for the former, while over 600.000 cases for the latter has been included in the dataset aggregating data from different bank sources. Each row represents a monthly snapshot of a loan, tracked over time to predict payment delays. Key columns include *Loan Identifier* for unique loan identification, *Originator* for the associated bank, and *Pool Cut-off date* for data registration timing of each observation. Other variables pertain to borrowers or loan characteristics, detailed in the following report section.

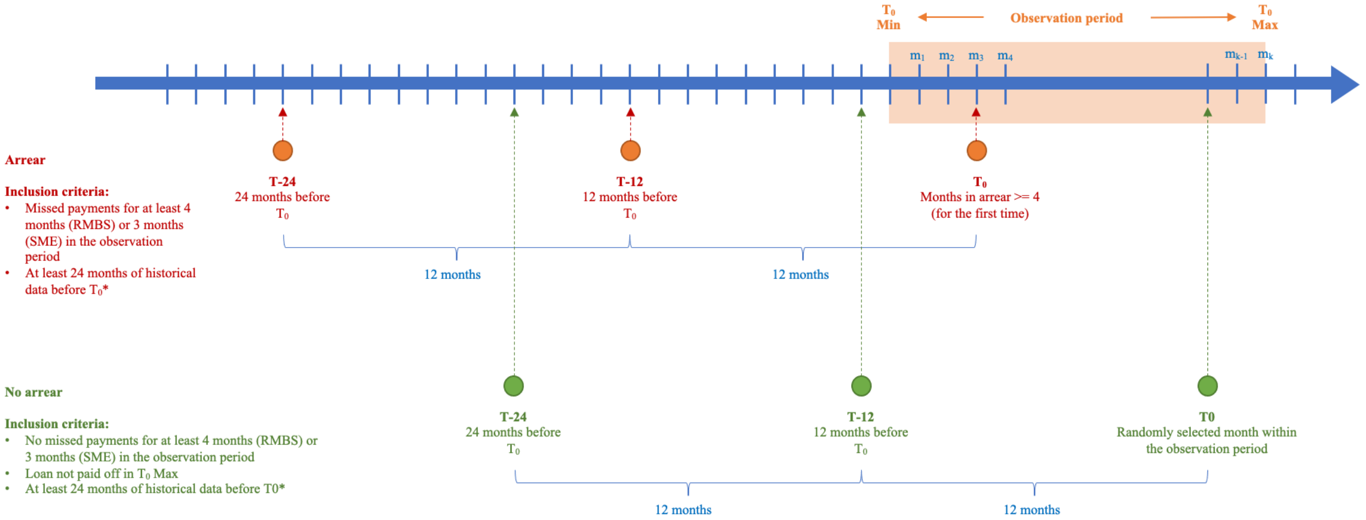
As already discussed, the focus of this work shifts from defaults to payment delays, specifically measuring the number of months in past-dues. The new definition of default and the line drawn between 90 days past due and non-performing are consistent with the choice made in this study. In particular, we have verified that our target variable was a client when it simultaneously exceeds, for more than 90 consecutive days, the absolute threshold: 100 euros for retail exposures; 500 euros for other non-retail exposures, and the relative threshold: 1% of the total amount of all exposures arising from the relationships that the customer has with the bank. The threshold for past-dues is set at four months for RMBS loans and three months for SME loans. This decision enhances the ability to identify critical situations before defaults occur and optimizes intervention strategies to manage payment delays and prevent potential defaults. Given the peculiar features of the two cases, data restructuring has been carried out differently for RMBS and SME cases. Further details are provided here below.

With reference to the RMBS subsample, the observation period for the analyzed phenomenon was set to 2022, with the previous two years used to predict payment delays of four months or more. The main steps included creating the target dummy (0/1) variable for past-dues based on evidence of past-due presence in 2022 identifying the first past-due date, and reconstructing predictive variable values accordingly, registering the data 12 and 24 months before the first evidence of past-due. It is important to note that only cases with at least 24 months of historical data previous to the first past-due identification have been taken into account in the analysis. Similarly, to what has been discussed for the RMBS, data for SMEs has been restructured identifying the first past-due in 2022 (assuming 3 months of delay in payments) and then all the other variables have been dynamically restructured.

More specifically, the inclusion criteria for the past-due case are the missing payment for more than 4 months (RMBS) or 3 months (SME) for the first time in 2022 and the availability of at least 24 months of historical data, given the data of first past-due. Simmetrically, non past-due observations have been identified if not payments have been missed in the observation period and having 24 months of available historical data. Furthermore, for non past-due cases random sampling has been applied to rebalance the dataset: more specific details will be given below.

A diagram representing the above-described process is available in Figure 1.

Figure 1: Workflow of the KPIs creation and sampling process



3.2 Feature Engineering

After having restructured the data, an appropriate phase of feature engineering has been carried out in order to enhance the quality and depth of the available data for the following modeling step. More specifically, the variables in the dataset could be classified into two broad groups:

- Static Variables - These variables have a single value for each loan (numeric or categorical) throughout the observation period. They are usually related to the borrower's demographic information or specific loan characteristics. Static variables are useful in the model construction phase to differentiate using structural characteristics that may indicate a higher propensity for payment delays. Among the static variables there are - for example - the type of the borrower (RMBS), the nationality (RMBS), the credit quality (RMBS), the geographic area (RMBS and SME), NACE code industry (SME) and purpose of the loan (RMBS and SME).

- Dynamic Variables - These variables change over time and capture variations in the loan flow elements or the credit situation of the loan holder(s). The reference value for dynamic variables might be the value 12/24 months before the past-due or an index calculated during the observation periods. Some of the dynamic variables are the loan to value (RMBS), number of months in past-due (RMBS and SME), maximum number in past-due (RMBS and SME), borrower deposit amount (SME) and the ratio between the average past-due value and the average installment. More specifically, some of the included dynamic variables are coming directly from the dataset, while most of them have been computed as KPIs or ratio mainly using original variables like the installment value, the number of months in past-due, the past-due amount: starting from these values several metrics has been calculated (ratio of means, measures of variability, maxima and minima).

3.3 Data Rebalancing

Before moving to the actual description of the applied methodology, it is worth underlying that the restructured dataset shows a very strong imbalance in the classes of the target variable (past-due). More specifically, the proportion of positive cases, those facing past-due in 2022, is less than 0.05% for the RMBS subsample and 2.22% for the SME case. This evidence could potentially bias the testing of the new algorithm because it is extremely likely - in presence of usage of unbalanced dataset for a classification problem - to overtrain the ability of detecting the majority class, while learning much worse the specific features for the minority class.

For the aforementioned reasons, a specific rebalancing strategy has been implemented to define the final dataset for the model testing phase. In particular, a random undersampling technique has been applied to the majority class, achieving a 1/20 ratio between class in the end: evidence of the effectiveness of a similar approach has been discussed by Hasanin and Khoshgoftaar (2018) in a simulated experiment on class imbalance. Despite still having a quite unbalanced dataset, this intervention on the original sources is aimed at obtaining a more balanced dataset and to consequently let the algorithms being more effective in learning better, while training, the relationships that link the features with the minority class of the target variable.

4 Methodological Framework

In this section of the work, the methodological approach to the modeling problem will be described. As pointed out in the literature review the two main approaches to model a credit risk problem are the supervised one (classical as well as Machine learning based) and unsupervised. The main idea of this application is to merge the two solutions in order to improve the performance of both methodologies.

4.1 Description of the Algorithm

More specifically, the algorithm wants to integrate two tree-based models, namely a Random Forest (supervised block of the model) with an Isolation Forest (unsupervised part of the same): the former will serve the purpose of modeling the classical classification objective, while the latter will be used as anomalies detection tool.

The key steps and rationale behind this integrated model are detailed below:

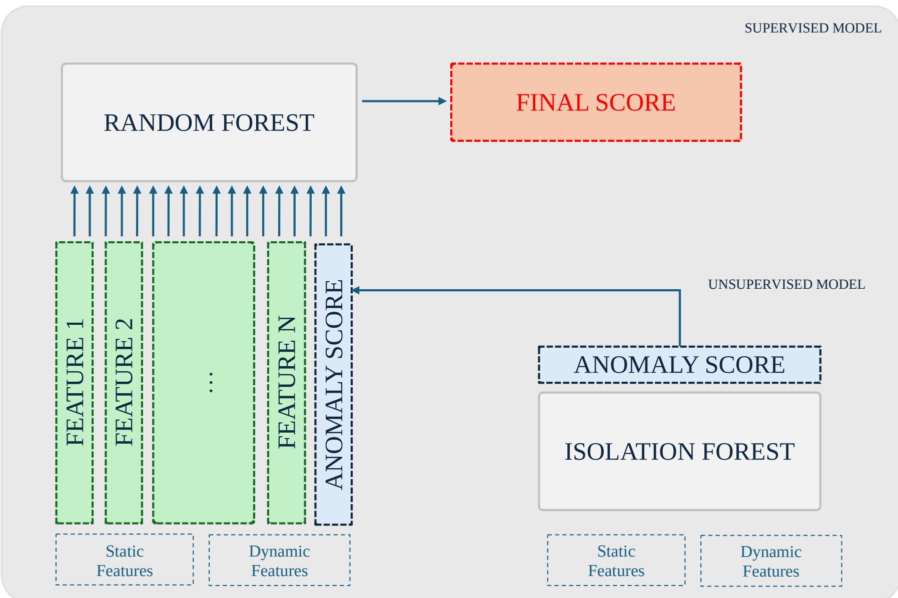
- Creation of the Unsupervised Isolation Forest Model for anomalies detection - All previously mentioned variables were used as inputs for the Isolation Forest model to estimate an anomaly score for each observation. The target variable (past-due information) was not included, focusing solely on identifying anomalous cases regardless of their connection to payment delays. The anomaly score has been included as extra predictor variable in the Random Forest Classifier.
- Creation of the Supervised Random Forest Model for the classification - As discussed above, a Random Forest model was selected due to its effectiveness in handling missing values and its proven performance in similar classification applications, as highlighted in the literature review.

At a broad level, the algorithm of Random Forest (Brieman, 2001) is a tree ensemble learning method, based on the idea of growing in parallel multiple trees (either classification or regression trees) on bootstrapped sample and using a random selection of the original features set. The predictions of the different trees are aggregated using a majority voting scheme (in case of a classification problem) or averaging (in the case of a regression problem). This method proved to be very effective in a lot of data science application, mainly for the extremely good ability in limiting overfitting and handing missing data.

Similarly, Isolation Forest (Liu, 2008) is an algorithm based on the detection of anomaly points using binary classification trees: in particular, the method is based on the applications of recursive splits of the dataset using features of the data at random and generating an anomaly score to quantify how a certain element is different from the rest of the data points.

From a theoretical standpoint, the integrated approach aims to improve prediction accuracy by including an additional variable that captures relevant anomaly information regarding each client’s credit behavior before the onset of payment delays. The proposed approach could be considered theorically sound, given similar implementation in related domain as in Zakrzewska (2007), Bijak and Thomas (2012) and Bao *et al*. (2019), despite the different types of algorithms implemented. The experimental application of this approach yielded excellent prediction results for both RMBS and SME loans, achieving a high balance in performance. More specific details regarding the performance of the proposed framework will be described in the following section. For the sake of clarity, a diagram representing the modeling approach is reported Figure 2.

Figure 2: Conceptualization of the proposed algorithm



In the following paragraph the results of the testing and benchmarking of the algorithm will be presented to assess its effectiveness in terms of performance, in this section. More specifically, the novel model has been benchmarked with different algorithms, both classical as well as Machine Learning based to gain a complete and multifaceted assessment of its performance. The performance of the different algorithms has been assessed using hold-out approach (75% of the observation has been used for the training of the algorithm, while the remaining 25% for testing on fresh sample). A complete list, along with a brief description of the algorithm, is presented in Table 1.

Table 1: Descriptions of tested algorithms

Model	Description
Logistic Regression	A statistical model that uses a logistic function to model the probability of a binary phenomenon (0/1)
Logistic Regression with Regularization	An extension of the Logistic Regression model that includes types of penalization (L1, L2, or ElasticNet) on coefficients to prevent overfitting and improve the generalizability of a classification model. In the case under analysis, ElasticNet has been implemented
Random Forest	An ensemble learning model based on the parallel construction of multiple decision trees with the aim of reducing overfitting problems
XGBoost	A gradient boosting (ensemble) algorithm based on the sequential construction of decision trees
H2O AutoML Model	An automated machine learning framework that explores various models and data pre-processing techniques to find the best possible model such as GLM (Generalized Linear Models, DRF (Random Forest & Extremely Randomized Trees), XGBoost, GBM (Gradient Bosteed Methods), Deep learning (Fully connected multilayer ANNs) and StackEnsemble. This solution will be tested to (i) validate the results obtained from the Random Forest and XGBoost algorithms and to (ii) include a performance benchmark coming from an automatic yet robust and performative modeling framework

4.2 Hyperparameters tuning

When building and assessing the performance of a Machine Learning model, it is extremely important to perform the tuning of hyperparameters: this is because the final effectiveness of the algorithm massively depends on the combination of the different tunable parameters of the different models.

For each of the included models, different hyperparameters' configurations have been tested and results have been validated using a 5-fold Cross Validation. The validation of the hyperparameters has been conducted through the implementation of Random Discrete search, uniformly sampling from a grid that encloses all the possible combination of hyperparameters.

All the models have been trained and tested using the H2O framework's for excluding any possible external bias related to the developer of the library or package.

The selection of the optimal hyperparameter combination for each algorithm was based on maximizing the Area Under the ROC Curve (AUC) metric.

This metric, indeed, is particularly useful in comparing models with different hyperparameters' configurations and it is independent of the threshold value set for classifying positive and negative cases, unlike other metrics such as sensitivity, specificity, accuracy, and F-measure.

For Logistic Regression with regularization, after initially employing a grid search with commonly adopted penalization degrees, manual testing of specific regularization values was conducted to gain greater sensitivity to the final output. However, it was observed that the final output exhibited minimal changes in performance even to significant variations in the penalization degree.

Given the experimental nature of this work, more specific information on the tuning of hyperparameters of the Supervised-Unsupervised model will be provided here below.

Regarding the Random Forest model, optimization was performed through a grid search of the following hyperparameters, limited to these values:

- Max Depth: 3, 5, 10, 20, 30

- Mtries (sampling column): 5, 10, 20
- Sample rate (sampling row proportion): 0.5, 0.632, 0.75
- Ntrees: 100, 200, 500

With reference to the Isolation Forest, it is extremely important to highlight that the default setting of the hyperparameters has been used given the unsupervised nature of the algorithm. This approach has been followed both for the RMBS subsample as well as for the SME.

Once selected for each of the tested models, the best configuration of the hyperparameters assessment on the test set has been applied. More details will be given in the following paragraph.

4.3 Validation Strategy of the tested algorithms

The current section of the work will present the approach implemented to validate the different algorithms. More specifically, following the usual procedures to validate a classification model, the algorithms have been compared according to several metrics that are summarized here below:

- Number of False Positives
- Number of False Negatives
- Precision
- Sensitivity
- Specificity
- AUC (Area under the curve of the Receiver Characteristic Operating curve)

It is important to note that the accuracy metric computed as proportion of the cases correctly classified into their respective classes, despite being widely used in classification problems, is extremely sensitive to the set threshold to classify the cases into the positive or negative class.

For this reason, a more exhaustive and less sensitive measure, like the AUC, will be used to select the most performing model.

The AUC, area under the ROC curve, is indeed computed by varying all the possible values of the classification threshold and then computing the values of specificity and sensitivity before plotting them, providing in the end a more holistic validation of the algorithm[1].

It is worth noting that for all the models the threshold for the different metrics obtained from the Confusion Matrix is reported: as an overall approach, the threshold has been selected to balance the sensitivity and specificity of the prediction through the maximization of the Youden's index[2].

In the next pages detailed results on all the previously mentioned metrics will be provided both for RMBS as well as for SME.

In this section the testing results for the two different subsamples will be presented along with the rationale behind the choice of the best model. Table 2 and Figure 3 report all the detailed performance metrics for the RMBS sample.

Table 2: RMBS - Performance metrics for the validated models (computed on 9580 cases of which 46 are past-dues)

Model	Threshold	False Pos.	False Neg.	Precision	Sensitivity	Specificity	AUC
Logistic Regression	0.006	1066	12	0.031	0.739	0.888	0.831
H2O Auto ML (GLM)	0.004	1508	7	0.025	0.848	0.842	0.863
Random Forest + Isolation Forest	0.006	1519	8	0.024	0.826	0.841	0.877
Pen. Logistic Regression	0.003	2457	5	0.016	0.891	0.742	0.851
XGBoost	0.001	1512	10	0.023	0.783	0.841	0.845

[1] the AUC metric ranges from 0 to 1. A model with an AUC of 0.5 is extremely poor (random guess), while an AUC of 1 represents the perfect model. In practice, values of AUC greater than 0.75 characterize good classification models

[2] the Jouden's index is computed as $J = Sensitivity + Specificity - 1$

Figure 3: RMBS - Performance comparison for the validated models (Specificity is reported in green, Sensitivity is reported in red, AUC is reported in blue)

As it is possible to note from the results, the proposed model seems to be very performative with respect to most of the metrics included in the analysis. Looking at the AUC, the Random Forest + Isolation Forest (RF+IF from now on) algorithm outperforms all the other tested ones, scoring a 0.877 of AUC compared to the second-best model that shows a value of 0.863 on the same metric. This result shows that the model proves quite good at detecting both the positive as well as negative class.

It is true that - by focusing the attention on the number of False Negative (past-due cases which are predicted as not in past-due) - the algorithm with the best performance is the Penalized Logistic Regression (only 5 cases are false negative); however, this evidence is counterbalanced by a very high number of False Positive cases (more than 2400 false positive).

Since the scope of the algorithm is to have a relatively good balanced in predicting both the classes under analysis, it was considered not advisable to select as best model one with such a high number of false positive cases because it could trigger in practice a too harsh contract revision policy from the institute.

For the sake of completeness, it is important to report that the same performance metrics have been computed setting the classification threshold through the maximization of the F1 score[3], a performance metric widely used in case of unbalanced dataset. However, when setting the threshold in this fashion the number of False Negative increases to 34 in the case of the most performative algorithm - RF + IF (according to the AUC) - making this choice not suitable at all from a practical standpoint.

Given all the evidence previously detailed, the RF+IF seems the best model in terms of balance between different metrics, electing it as most suitable for a real case application scenario. Detailed values are reported in the Appendix (Table 7).

Similarly, to what has been discussed for the RMBS sample, Table 3 and Figure 4 report the performance results for the SME data points.

In general, all the metrics are slightly better for the SME case compared to the RMBS but there are a lot of similarities between the two sub samples. Assuming the same approach followed for RMBS, the metrics reported in the table are those obtained setting the threshold when maximizing the Youden's index.

More specifically, the most performative model in terms of AUC is still the RF +IF (0.957) followed by the H2O Auto ML (0.95) and the XGBoost (0.93).

Regarding the number of False Positive, the RF + IF algorithm is still the best one in the group (only 2 cases are misclassified as false negative); while the lowest value of false positive could be found when implementing the Penalized Logistic Regression (31 misclassified cases).

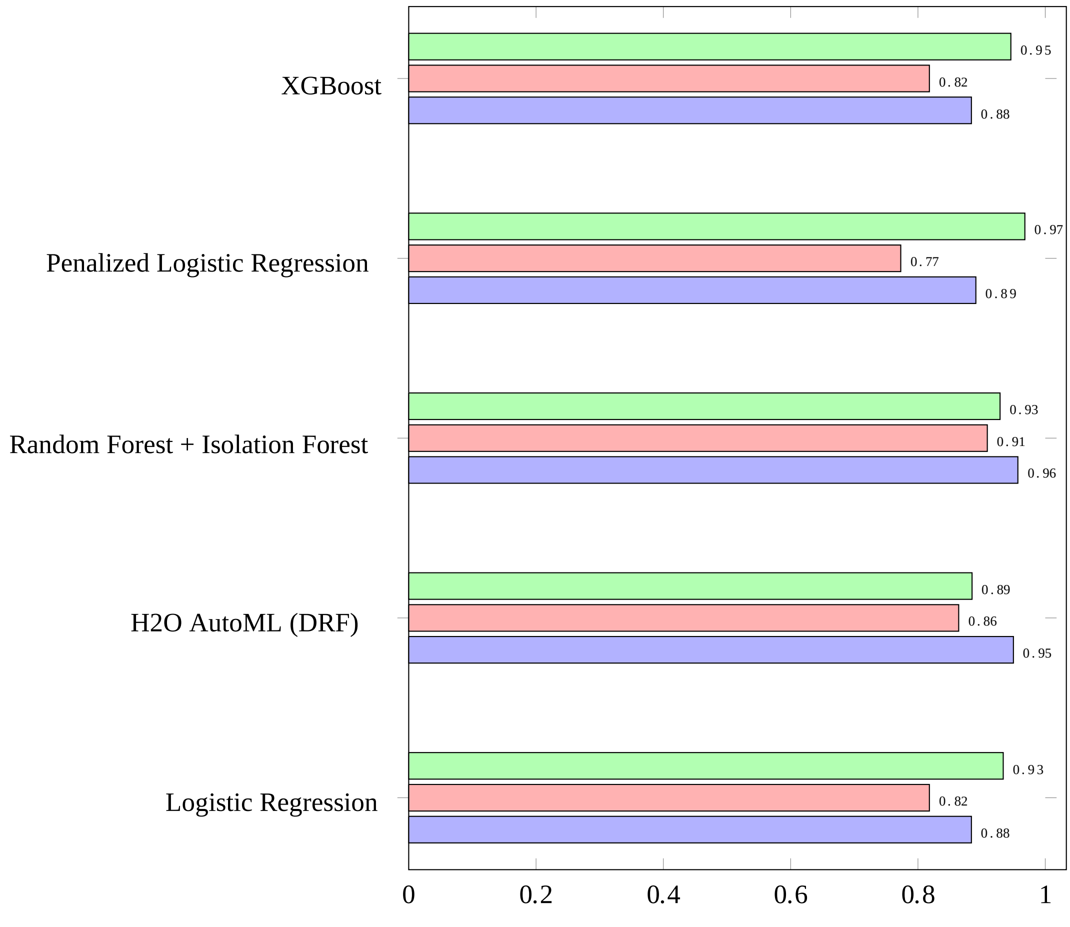
[3] the F1 score is computed as $\frac{2tp}{2tp+fp+fn}$, where tp are the true positive, fp are the false positive and fn are the false negative

Also in this case, the performance has been double checked computing the same performance metrics but setting the threshold through the maximization of the F1 score: however, similarly to what has been discussed for the RMBS case, the absolute number of false negative increased for all the algorithms suggesting to discharge this approach. Detailed results are provided in Table 8

Table 3: SME - Performance metrics for the validated models (computed on 993 cases of which 22 are past-dues)

Model	Threshold	False Pos.	False Neg.	Precision	Sensitivity	Specificity	AUC
Logistic Regression	0.024	64	4	0.22	0.818	0.934	0.884
H2O Auto ML (DRF)	0.026	112	3	0.145	0.864	0.885	0.95
Random Forest + Isolation Forest	0.036	69	2	0.225	0.909	0.929	0.957
Pen. Logistic Regression	0.041	31	5	0.354	0.773	0.968	0.891
XGBoost	0.032	52	4	0.257	0.818	0.946	0.93

Figure 4: SME - Performance comparison for the validated models (Specificity is reported in green, Sensitivity is reported in red, AUC is reported in blue)



4.4 Random Forest + Isolation Forest, Variable Importance and Partial Dependence Plot

To complement the performance analysis just exposed in the previous paragraphs, the variable importance has been computed in order to understand which are the variables that most impact on the past-due both for RMBS as well as for the SME cases. As mentioned in the literature review, machine learning based methodologies are usually, like in the case under analysis, better in terms of performance compared to classical models but one of the main drawbacks of these algorithms is the lack of interpretability of results. More specifically, when dealing with regression models it is easy to assess the effect of one feature on the target variable, both in terms of sign as well as magnitude, by interpreting the coefficient; this is not possible with most of the machine learning methods: for this reason, several methodologies have been developed to indirectly estimate these effects.

Here below, the variable importance in predicting the past-due for RMBS and SME is reported (the ten most important variables are shown in Table 4). As it is possible to see, the variables that are most important in predicting the past-due for RMBS loans are geographic area, the age of the debtor, some ratios and KPIs (std. dev. of the ratio past-due/installment; max number of months in past-due etc.), the current interest rate and the isolation forest anomaly score. On the other hand, for the SME cases, the most important variables turn out to be the industry of the company, the number of months in past-due, the past-due balance and the geographic area. In this case, the anomaly score of the isolation forest is relevant but it is not included in the ten most important features. In order to understand how each value or level of these variables could potentially impact the past-due, partial dependence plot (PDP) are shown in Figure 5, Figure 6 and Figure 7. For example, it is possible to note (Figure 5) that the Isolation Forest Anomaly Score has a quite weak positive effect on the probability of past-due; similarly, for SME higher number of months with positive past-due value (last year) increases the likelihood of missing the monthly payment.

Table 4: Variable Importance (RMBS and SME)

Variable Importance (RMBS)	**Percentage**
ST_geographic_region	11.0%
24_LY_std_past-due_over_installment	2.8%
ST_age	2.8%
12_LY_max_num_months_past-due	2.5%
24_current_interest_rate	2.2%
24_LY_max_num_months_past-due	2.2%
IF_anomaly_score	2.1%
12_number_months_past-dues	2.1%
24_current_interest_rate_margin	2.1%
12_LY_n_months_positive_past-due	2.0%

Variable Importance (SME)	**Percentage**
ST_ industry_code	18.4%
12_LY_n_months_positive_past-due	6.3%
12_LY_n_months_positive_past-due_balance	5.4%
24_mean_total_past-due_balance	4.6%
24_ LY_n_months_positive_past-due	4.4%
24_LY_n_mnoth_positive_past-due	4.0%
12_ mean_total_past-due_balance	3.2%
ST_geographic_region	2.9%
24_st_dev_tot_past-due_balance	2.3%
24_max_tot_past-due_balance	2.1%

Figure 5: RMBS – Partial Dependence plot (Isolation Forest Anomaly score)

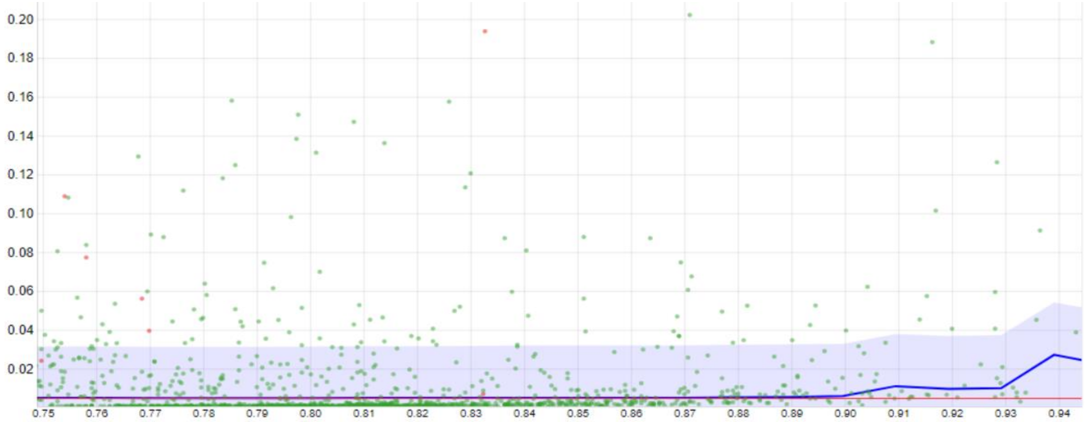


Figure 6: RMBS – Partial Dependence plot (Ratio between Standard Deviation of Past-dues value and the mean installment amount)

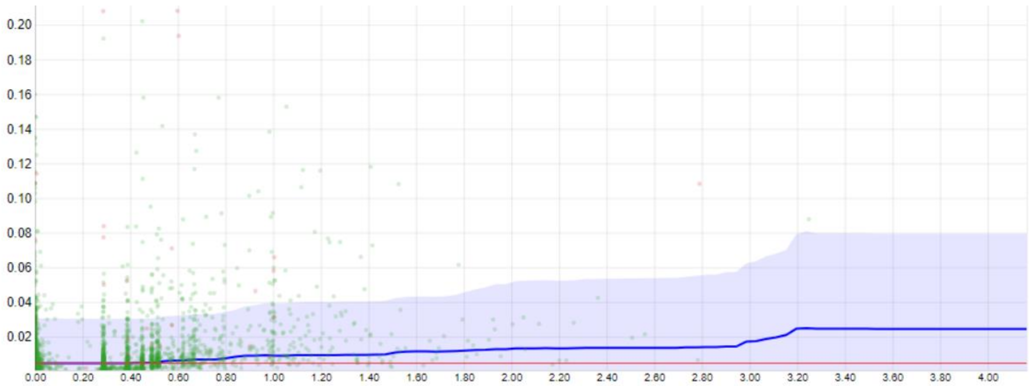
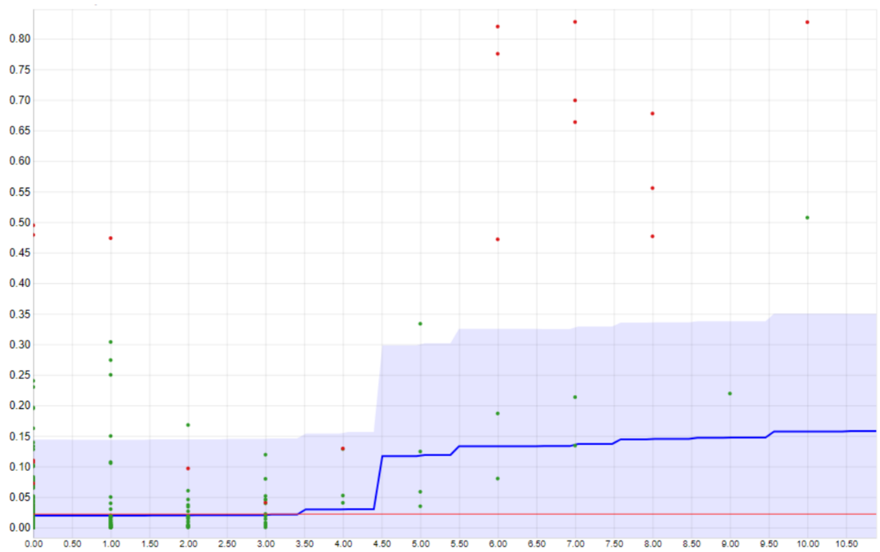


Figure 7: SME – Partial Dependence plot (Number of months with positive past-due value (last year))



4.5 Algorithm Validation on 2023 Data

With the purpose of further validation, the selected algorithm has been tested with specific reference to its robustness and effectiveness on new observed cases, coming from 2023 data. This activity is mainly aimed at further testing the selected model but – at the same time – applying it into a realistic scenario, very similar to the one to which it will be exposed once deployed in practice. Table 5 shows the performance metrics computed on 2023 data both for RMBS and for SME.

Table 5: RMBS and SME performance metrics for 2023 data

Model	Threshold	False Pos.	False Neg.	Precision	Sensitivity	Specificity	F-Measure	AUC
RMBS – Random Forest + Isolation Forest (computed on 30583 cases of which 207 are past-dues)	0.024	64	4	0.22	0.818	0.934	0.346	0.884
SME – Random Forest + Isolation Forest (computed on 2835cases of which 75 are past-dues)	0.036	52	4	0.257	0.818	0.946	0.391	0.93

As it is possible to see from the results reported in the table, the algorithm seems to be quite good at predicting the past-due of the customers: by looking at the number of False Negative in the case of RMBS only 4 have been misclassified and 4 also for SME. Focusing the attention on other performance metrics, it is worth noting that the value of the AUC is very good (0.884 in case of RMBS and 0.93in case of SME), aligning with the performance results in the testing set. Likewise, the values of Sensitivy and Specificity are satisfactory being respectively 0818 and 0.934 for RMBS and 0.818 and 0.946 for SME.

5 Final Remarks

It is possible to assert, given all the previously reported results, that the developed model seems to be a good and well-suited altervative to more diffused methodologies in the credit risk estimation domain. From a technical standpoint, the model has achieved very good performance under all the considered criteria, outperforming in the most relevant ones all the challenging methodologies both for RMBS as well as SME. In addition, by testing the model on fresh data (2023) the level of its effectiveness has been validated, confirming the robustness of the approach that strengthens the flexibility of the supervised classification model (Random Forest) with the anomalies detection properties of the unsupervised one (Isolation Forest).

From an operational standpoint, this new model could be implemented in real application to help the management in monitoring the current loan portfolio and consequently taking informed decisions on specific case. It is, indeed, important to remark that this work is innovative not only in terms of implemented methodology but also in terms of the targeted phenomenon (past-due prediction). The past-due prediction could be then used to foresee the eventual default, allowing the decision makers to put in practice specific actions just for a circumscribed subgroup of customers that are more likely – according to the model – to not repay entirely the loan.

As a final remark, an application of the developed algorithm will be briefly discussed hereafter. It is relevant to remember that the output of the model – as it is typical for a binary classification algorithm – is a numeric score ranging from 0 to 1: the higher this value, the more likely the past-due is. As described above, it is possible to convert this score into two classes (past-due and no past-due) depending on the set threshold. Alternatively, it is possible to use this score to define risk classes that could be more helpful in practice to have a better level of detailed of the positions that need to be monitored carefully.

Table 6 reports the data of risk classes for RMBS loan. From a technical standpoint, the classes are not overlapping (each observation will be in one class only) and strictly increasing in terms of associated past-due probability, with class 7 being the one with the highest risk. The classes have been built using statistical criteria starting from the entire distribution of predicted scores. For instance, considering the first three riskiest classes (risk class 5 up to risk class 7) it is possible to correctly detect roughly 67% of the total past-due cases, proving this approach to be very handy for a practical sperimentation to new cases.

Table 6: RMBS risk classes

Risk class	Tot. Loan	N. no past-due	N. past-due	% past-due in each class	% detected past-due (n past-due class/ tot. past-due)	Cumulative % detected past-due	Rel. dimension of the class	Cumulative % of loan
7	172	155	17	9.88%	37.0%	37.0%	1.8%	1.8%
6	288	279	9	3.13%	19.6%	56.5%	3.0%	4.8%
5	288	283	5	1.74%	10.9%	67.4%	3.0%	7.8%
4	480	475	5	1.04%	10.9%	78.3%	5.0%	12.8%
3	960	956	4	0.42%	8.7%	87.0%	10.0%	22.8%
2	2784	2781	3	0.11%	6.5%	93.5%	29.1%	51.9%
1	4608	4605	3	0.07%	6.5%	100.0%	48.1%	100.0%
Total	**9580**	**9534**	**46**	**0.48%**	100.0%		100.0%	

In the field of banking and financial services, a critical focus for industry stakeholders is the accurate prediction of probability of default (PD) and the effective classification of raw data into risk classes. This study addresses the challenge of predicting PD for Residential Mortgage-Based Securities (RMBS) and Small and Medium Enterprises (SMEs) within the Italian banking sector. It presents an innovative methodology that combines a Random Forest classification model with an Isolation Forest anomaly detection technique, trained on a comprehensive dataset covering the period 2020-2022.

What sets this research apart is its unique emphasis on the delinquency status of RMBS and SME clients as the primary target variable. By focusing on arrears rather than the broader concept of PD, this approach provides deeper insights into customer financial stress, facilitating proactive monitoring and intervention strategies for decision-makers.

The ultimate goal of this study is to develop a robust, practical algorithm capable of accurately predicting both individual customer and corporate delinquencies, thereby improving management decision making. Empirical results highlight the superiority of the proposed framework over traditional statistical and machine learning algorithms in credit risk modelling, demonstrating robust performance validated with 2023 data and confirming its operational readiness.

However, when selecting and deploying a machine learning model such as the one proposed in this article, there are a number of critical aspects that need to be considered. Practitioners must consider that validity of the model is closely linked to the quality and representativeness of the data set used for training (2020-2022). If historical data does not accurately reflect future economic conditions or changes in customer behavior, predictions may be inaccurate. Although the model performed well on test data and was also validated on 2023 data, there is always a risk of overfitting, especially with complex machine learning models that are based on many features. In order to avoid performance degradation on new, previously unseen data, it’s always recommended to retrain the model, at least on annual basis.

Random forest and isolation forest models are known to be less interpretable than simpler models. This lack of transparency can make it difficult for decision makers to understand and trust the model's predictions, even if we might use XAI tools (such as partial dependence plots) to improve interpretability, as shown in the article.

The division into risk classes and the definition of thresholds for classification (past due and not past due) can introduce bias. If the thresholds are not properly calibrated, classification errors can occur, leading to incorrect management decisions. Isolation Forest is designed to detect anomalies, but may have difficulty detecting anomalies in contexts with high variability or complex data patterns. This can affect the accuracy of predicting failure. Models may not be able to adapt quickly to sudden changes in market conditions, such as financial crises or regulatory changes, limiting their effectiveness in situations of economic stress.

Implementing and maintaining these complex models can be costly for financial institutions, both in terms of computational resources and the expertise required to run and update the models. Although the model has been validated with fresh data from 2023, its performance may not be fully generalisable to other geographical contexts or sectors beyond Italian banks.

In conclusion, financial institutions are encouraged to adopt advanced credit risk models that combine Random Forest classification with Isolation Forest anomaly detection. This recommendation is based on the superior performance of the hybrid model in predicting delinquencies, suggesting that it could improve the accuracy of credit risk assessments. Implementation of the developed model can significantly improve the monitoring of loan portfolios. By accurately identifying loans at higher risk of delinquency, banks can proactively mitigate potential losses. The model's ability to segment customers into risk classes enables more targeted and effective management strategies.

By focusing on predicting delinquencies rather than defaults, the model provides a nuanced understanding of borrowers' financial stress. This enables financial institutions to design and implement early intervention strategies, such as restructuring loans or offering financial counselling to at-risk borrowers, potentially preventing defaults.

Regulators could consider updating guidelines to require the use of sophisticated credit risk models. The effectiveness and robustness of the model in predicting delinquencies could help financial institutions meet regulatory requirements more efficiently and accurately.

The classification of loans into risk classes allows banks to optimise the allocation of resources. Higher-risk loans can be monitored more closely, while lower-risk loans require less oversight, resulting in more efficient use of human and technology resources. Detailed risk classifications allow financial institutions to refine their risk-based pricing strategies. By aligning loan pricing with the predicted risk of default, banks can better balance risk exposure and profitability.

Understanding the likelihood of default enables more effective customer engagement. Banks can offer personalised communication and support to high-risk customers, improving satisfaction and potentially reducing churn.

To maintain the accuracy and effectiveness of the model, financial institutions should establish policies for continuous data collection, updating and analysis. The model's reliance on comprehensive and recent data (e.g. 2020-2022) underscores the importance of a data-driven approach.

Investment in staff training is critical for banks to effectively use advanced credit risk models. Appropriate training ensures that the insights provided by the model are correctly interpreted and applied in the decision-making process. In addition, the success of the model encourages further collaboration between academic researchers, financial institutions and technology providers. Continuous innovation and validation of such models is essential to keep pace with evolving market conditions and emerging risks.

By adopting these policy implications, financial institutions can use the developed model to improve their credit risk management practices. This adoption could lead to more stable and resilient financial systems and improve overall efficiency, compliance and customer relations in the banking sector.

Appendix

Table 7: RMBS - Performance metrics for the validated models, threshold set maximizing F1 score (computed on 9580 cases)

Model	Threshold	False Pos.	False Neg.	Precision	Sensitivity	Specificity	F-Measure	AUC
Logistic Regression	0.076	78	36	0.114	0.217	0.992	0.149	0.831
H2O Auto ML (GLM)	0.086	42	39	0.143	0.152	0.996	0.147	0.863
Random Forest + Isolation Forest	0.067	67	34	0.152	0.261	0.993	0.192	0.877
Pen. Logistic Regression	0.088	21	39	0.25	0.152	0.998	0.189	0.851
XGBoost	0.026	62	35	0.151	0.239	0.993	0.185	0.845

Table 8: SME - Performance metrics for the validated models, threshold set maximizing F1 score (computed on 993 cases)

Model	Threshold	False Pos.	False Neg.	Precision	Sensitivity	Specificity	F-Measure	AUC
Logistic Regression	0.152	8	9	0.619	0.591	0.992	0.605	0.884
H2O Auto ML (DRF)	0.299	2	9	0.867	0.591	0.998	0.703	0.95
Random Forest + Isolation Forest	0.342	1	9	0.929	0.591	0.999	0.722	0.957
Pen. Logistic Regression	0.131	11	8	0.56	0.636	0.989	0.596	0.891
XGBoost	0.146	5	8	0.737	0.636	0.995	0.683	0.93

Table 9: RMBS – List of Static Features considered in the models

Feature name	**Description**
ST_Borrower Type	Debtor type
ST_Number of Debtors	Number of debtors
ST_Borrower's Employment Status	Debtor's employment status
ST_First-time Buyer	First-time Buyer
ST_Class of Borrower	Class of debtor
ST_Primary Income	Primary debtor's annual income
ST_Secondary Income	Secondary debtor's annual income
ST_Resident	Residence
ST_Origination Channel / Arranging Bank or Division	Sales channel, arranging bank or division
ST_Purpose	Purpose of financing
ST_Amount Guaranteed	Guaranteed amount
ST_Loan Currency Denomination	Currency
ST_Original Balance	Initial amount
ST_Fractioned / Subrogated Loans	Fractioned loan
ST_Repayment Method	Repayment method
ST_Payment Frequency	Installment frequency
ST_Type of Guarantee Provider	Type of guarantor
ST_Guarantee Provider	Name of guarantor
ST_Pre-payment Amount	Amount of prepayments or early reductions
ST_Interest Rate Type	Interest rate type
ST_Geographic Region List	Province code
ST_Property Type	Property type
ST_Original Loan to Value	Loan to value
ST_Valuation Amount	Original appraisal amount
ST_Additional Collateral Provider	Provider of additional real guarantees
ST_Income Verification for Primary Income	Primary debtor income certification
ST_Income Verification for Secondary Income	Secondary debtor income certification
ST_Valuation Date	Original appraisal date
ST_Shared Ownership	Shared ownership
ST_Restructuring Arrangement	Restructured loan indicator
ST_Property Rating	Property rating
ST_Lien	Mortgage grade
ST_Length of Payment Holiday	Duration of suspensions
ST_Interest Cap Rate	Interest rate cap
ST_Loan Term	Original loan duration
ST_Mortgage Inscription	Mortgage registration amount
ST_Mortgage Mandate	Mortgage registration mandate
ST_New Property	New property
ST_Prior Repossessions	Previous mortgage possession
ST_Principal Grace Period	Number of months of grace period
ST_Payment Type	Payment type
ST_Prepayment_ratio	Prepayment amount/Original balance ratio
ST_Tot_Income	Sum of Primary + Secondary income
ST_Age	Age of the borrower at t0

Table 10: RMBS – List of Dinamic Features considered in the models (each feature is measured at t-12 and t-24)

Feature name	**Description**
Current Balance	Outstanding debt balance
Payment Due	Contractual amount of the installment

Debt to Income	Installment to income ratio
Cumulative Pre-payments	Total prepayments or early reductions
Current Interest Rate Index	Reference rate
Current Interest Rate	Applied rate
Current Interest Rate Margin	Spread
Interest Rate Reset Interval	Rate review
Current Loan to Value	Current Loan to Value
Current Valuation Amount	Updated appraisal amount
Current Valuation Type	Type of updated appraisal
Current Valuation Date	Date of updated appraisal
Date Last in Arrears	Date since the debtor is in arrears
Arrears Balance	Balance of arrear amounts
Number Months in Arrears	Number of months in arrears
Arrears 1 Month Ago	Balance of arrear amounts recorded the previous month
Arrears 2 Months Ago	Balance of arrear amounts recorded two months earlier
Months in Arrears Prior	Number of months in arrears at the end of the month preceding the repayment date
LY_max_num_month_arrear	Maximum number of months in arrear (Last Year)
LY_N_month_pos_arrear	Number of months in which the arrears balance is positive (Last Year)
LY_max_balance_arrear	Maximum value of arrears balance (Last Year)
LY_N_balance_pos_arrear	Number of times the arrears balance is positive (Last Year)
LY_avg_arrear_over_payment	Average Arrears/average installment ratio (Last Year)
LY_std_ arrear_over_payment	Standard Deviation Arrears/average installment ratio (Last Year)
LY_Payment_Income_Ratio	Installment/Income ratio (Last Year)

Table 11: SME – List of Static Features considered in the models

Feature name	**Description**
ST_Geographic Region	Geographic province
ST_Obligor Legal Form / Business Type	Debtor type
ST_Borrower Basel III Segment	Segment to which the bank's client (debtor) belongs according to Basel III regulations
ST_Syndicated	Syndicated loan
ST_ Industry Code	Debtor's sector
ST_Original Loan Balance	Initial loan amount
ST_Securitised Loan Amount	Securitised loan amount, i.e., the outstanding debt at the securitisation date
ST_Purpose	Purpose
ST_Principal Payment Frequency	Frequency of principal payment
ST_Interest Payment Frequency	Frequency of interest payment
ST_Weighted Average Life	Weighted average life (considering the type of amortisation and the maturity date) at the pool cut-off date
ST_Prepayment Penalty	Prepayment penalties
ST_Interest Floor Rate	Interest rate floor (lower limit)

ST_Final Margin	Final spread
ST_Interest Reset Period	Reference index review interval
ST_Turnover of Obligor	Debtor's turnover
ST_Short Term Financial Debt	Short-term financial debts
ST_Earnings Before Interest, Taxes, Depreciation and Amortisation (EBITDA)	EBITDA
ST_Number of Employees	Number of employees
ST_EBITDA/Turnover	EBITDA/Turnover

Table 12: SME – List of Dinamic Features considered in the models (each feature is measured at t-12 and t-24)

Feature name	Description
Total credit limit granted to the loan	Credit limit granted to the loan
Total Credit Limit Used	Credit used
Borrower deposit amount	Borrower's deposit amount (current account balance)
Borrower deposit currency	Borrower's deposit currency
Loan Hedged	Loan protection to offset currency risk losses (underlying risk)
Current Balance	Outstanding debt
Maximum Balance	Maximum outstanding debt
Amortization Type	Type of amortization
Regular Principal Instalment	Principal installment
Regular Interest Instalment	Interest installment
Balloon Amount	A loan with a large final installment
Payment type	Payment method
Prepayment Penalty	Prepayment penalties
Current Interest Rate	Applied rate
Interest Cap Rate	Cap (upper limit of the rate)
Interest Floor Rate	Floor (lower limit of the rate)
Interest Rate Type	Type of interest rate
Current Interest Rate Index	Reference rate
Current Interest Rate Margin	Spread
Revised Interest Rate Index	Revised interest rate index (post option exercise)
Final Margin	Final spread
Interest Reset Period	Reference index review interval
Currency of Financials	Financial statement currency
Number of Days in Interest Arrears	Number of days in interest arrears
Number of Days in Principal Arrears	Number of days in principal arrears
Days in Arrears Prior	Number of days in arrears in the month preceding repayment
Sum_arrear_balance	Total arrear balance
Regular_instalment	Total installment
LY_N_month_pos_arrear	Number of months in which the arrear balance is positive (Last Year)
LY_N_balance_pos_arrear	Number of times in which the arrear balance is positive (Last Year)
LY_mean_arrear_balance	Average arrear balance (Last Year)
LY_std_arrear_balance	Standard deviation of arrear balance (Last Year)
LY_max_arrear_balance	Maximum arrear balance (Last Year)
LY_tot_interest	Total interest (Last Year)

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Interest rates, profitability and risk: Evidence from local Italian banks over the years 2006 - 2018

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Abstract

This paper studies the determinants of net interest margin and of the exposure to the interest rate risk of a sample of 125 local Italian banks during the period 2006-2018. Relative to prior literature, to take advantage of the unprecedented interest rate environment determined by European Central Bank (ECB)'s unconventional monetary policy measures, we consider two sub-periods: 2006-2011 and 2012-2018.
Banks' net interest margin increases with the intensity of maturity transformation, with a larger effect in the years 2012-2018, and with their exposure to interest rate risk. At this specific regard, we shed more light than previous studies by distinguishing among three sources of this risk, namely the one referred to the loans issuing and deposits collecting activity, the one stemming from the securities portfolio, and the one associated with derivatives positions.
Maturity transformation is associated with an increase in interest rate risk exposure, again with an impact that is stronger over the years 2012-2018. Funding from the ECB is associated with a higher interest rate risk exposure in the years 2006-2011, while it results in a reduction in the second part of the analysed period. We argue that ECB's (targeted) long-term refinancing operations lead to higher funding stability and strengthen banks' capacity to withstand potential upward shocks in interest rates. The opposite occurs for the deposits held by our sample bank at the ECB.

Keywords: Net interest margin; Interest rate risk; Maturity transformation; Unconventional monetary policy.

JEL Classification: G21; G32; E43; E52.

1. Introduction

Banks' exposure to interest rate risk is at the centre of the current debate on the financial stability of the euro area, due to the potential negative effects of the normalization of the European Central Bank's (ECB) monetary policy, which has raised the three benchmark rates by 450 basis points from the levels of July 2022.[1] The crisis of US Savings and Loan Associations in the 1980s has shown for the first time ever the systemic nature of the interest rate risk (Curry and Shibut, 2000). The collapse of the Silicon Valley Bank and the failure of Signature Bank, in early March 2023, again in the US, have recently reminded us of the adverse effects stemming from the combined impact of interest rate and liquidity risks when banks do not properly manage the maturity mismatch between their assets and liabilities in a context of rising rates.[2]

Understanding banks' actual exposure to interest rate risk is not only relevant from a financial supervision perspective but is also useful for predicting the potential effect of changes in monetary policy rates on the real economy (Van den Heuvel, 2012). The empirical evidence supporting the existence of the risk-taking channel of monetary policy focuses on credit risk (Altunbas *et al*., 2014; Jiménez *et al*., 2014; Paligorova and Santos, 2017). However, within the supervisory review and evaluation process (SREP), the assessment of interest rate risk exposure by supervisory authorities may lead to the so called additional Pillar 2 requirements (P2Rs), which, all else being equal, reduce banks' lending capacity.

To account for the changes in financial markets conditions of the years after the 2007-2008 global financial turmoil and the 2010-2011 euro area sovereign debt crisis, which were mainly induced by the monetary policy responses to those events, the Basel Committee on Banking Supervision (BCBS) updated in 2016 the standardized method introduced in 2004 to estimate banks' exposure to interest rate risk of the banking book[3] (BCBS, 2016).

Among the other things, the Committee proposed the adoption of six different interest rate shock scenarios to measure the impact of the interest rate risk. In 2017 the ECB conducted a stress test exercise to verify the sensitivity of a bank's banking book assets and liabilities and net interest margin to the six BCBS (2016)'s shock scenarios. In July 2018, the European Banking Authority (EBA) updated its guidelines on interest rate risk management, by also incorporating the same six shock scenarios. On October 20, 2022, the EBA also published new guidelines, replacing and updating those of 2018, and two technical regulatory standards, effectively introducing BCBS' provisions into the European Union.

The strong commitment by banking supervisory authorities and the new monetary policy stance have boosted further studies on interest rate risk-related issues (Molyneux *et al*., 2022; Hoffmann *et al*., 2019; Altavilla *et al*., 2018; Chaudron, 2018; Bednar and

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[1] At the time of writing, the decision regarding the last rate hike dates back to September 14, 2023, when the Governing Council decided to raise the interest rate on the main refinancing operations and the interest rates on the marginal lending facility and the deposit facility to 4.50%, 4.75% and 4.00% respectively, with effect from 20 September 2023. For details about the sequence of ECB's rates rises, please refer to the following link: https://www.ecb.europa.eu/stats/policy_and_exchange_rates/key_ecb_interest_rates/html/index.it.html.

[2] https://www.fdic.gov/news/speeches/2023/spmar2723.html#_ftn4

[3] In the rest of the paper by "interest rate risk (exposure)" we mean the sensitivity to changes in interest rates of the only the banking book and not also of the trading book.

Elamin, 2014). In this perspective, we have a twofold objective and provide a contribution to the two empirical research areas dealing with bank profitability and riskiness, respectively. First, we investigate the determinants of banks' profitability by specifically focusing on the impact of their maturity transformation and the associated exposure to interest rate risk on the net interest margin. Second, we study the factors that can explain banks' sensitivity to interest rates. We contribute to previous studies in these areas since, to the best of our knowledge, no paper has examined whether and how the adoption of unconventional monetary policies, and the consequent extraordinary financial markets conditions, have influenced how maturity transformation and interest rate risk exposure affect bank profitability, on the one hand, and the determinants of interest rate risk exposure, on the other. Furthermore, we focus on local banks, which have never been specifically investigated by prior studies.

To fill this gap, we examine 125 Italian banks during the period 2006-2018, of which 106 are limited liability cooperative banks, (90 "*banche di credito cooperativo*" and 16 "*banche popolari*"), with the remaining 19 having a joint-stock company legal form ("*società per azioni*"), and split our sample period in two sub-periods: first, the years from 2006 to 2011; second, those from 2012 to 2018, during which banks have been running their business under a scenario never experienced before, which was shaped by ECB's ultra expansionary monetary policy. In December 2011 and January 2012, the ECB launched the long-term refinancing operations (LTROs), followed in 2014 and 2016 by the first two series of targeted long-term refinancing operations (TLTROs). Furthermore, in June 2014, for the first time ever, the ECB decided to cut its deposit facility rate below 0%, to -0.1%, thus starting the so-called negative interest rate policy (NIRP).

These measures changed banks' liability structure (ECB, 2021), with impacts in terms of performance and stability, the analysis of which has in our view relevant implications for both industry and supervisors. We focus on Italian banks since the huge presence of intermediaries typically active in collecting financial resources through short-term (sight and savings) deposits and in issuing medium- and long-term loans, usually held until maturity, makes the Italian banking system an ideal context to tackle the issues mentioned above.

As far as the period of our investigation is concerned, a 12-year time horizon allows us to run our analyses under different financial markets conditions. We specifically refer to the different configurations of the yield curve over those years, especially with regard to the changes in its slope. Since, due to their traditional intermediation activity, our sample banks use to ride the yield curve, changes in the slope of this latter have a tremendous impact on their profitability and stability.[4]

Following the pioneer work of Flannery and James (1984), empirical studies typically measure interest rate risk exposure by estimating the sensitivity of bank equity returns to changes in interest rates. From a methodology perspective, we contribute to prior studies by adopting a duration gap approach, which is in line with the prudential regulation set by the Basel Committee on Banking Supervision (BCBS, 2004, 2006, 2016), and, at Italian national level, by the Bank of Italy's Circular 285/2013. We are motivated in doing so because of the importance to appropriately consider the impact on bank economic value of changes in interest rates in the case of banks running a traditional intermediation business, like those included in our sample.

The relevance of such risk measure has been recently stressed by Andrea Enria, Chair of the ECB Supervisory Board, in a speech at the Deutsche Bundesbank symposium "Bankenaufsicht im Dialog" on November 8, 2022. According to Mr. Enria, banks tend to assess their exposure to interest rate risk from a short-term income perspective.

Based on June 2022 data, supervised banks confirmed that their net interest income would react positively to a 200-basis point shock in the yield curve. Nevertheless, on average, the same shock would have a negative impact on banks' economic value, with the 20 most affected intermediaries experiencing reductions in their common equity tier 1 (CET1) ranging from 100 to 400 basis points. The impact would be larger for retail banks, due to a business model which rests on a longer duration gap.[5]

Our main results show that the intensity of maturity transformation contributes positively to banks' net interest margin and determines an increase in interest rate risk exposure of the banking book. As expected, this latter is also associated with a raise in banks' profitability, measured in terms of net interest margin. Banks' net interest margin increases with the slope of the yield curve, while it is positively affected by the rates level in the years 2006-2011 and negatively during the period 2012-2018, thus entailing in this second case significant frictions in asset and liability re-pricing, based on which interest rate increases compress banks' net interest margin in the short term.

The ECB funding is associated with higher interest rate risk exposure in the years 2006-2011, while it results in a reduction of the negative impact on banks' economic value in the second part of the period under analysis. Therefore, in the second period it seems that the contribution of ECBs' LTROs and TLTROs in terms of our sample banks' funding stability translates into a superior capacity to withstand potential upward shocks in interest rates. The opposite occurs for the deposits held by our sample banks at the ECB: they reduce interest rate risk over the years 2006-2011, whereas are positively associated with banks' risk exposure during the years ranging from 2012 to 2018.

The remainder of the paper is organized as follows: section 2 contains an analysis of the main studies on the determinants of banks' net interest margin and interest rate risk exposure; section 3 presents the empirical investigation, examining the methodology and discussing the variables used in the analysis and developing four hypotheses to test; section 4 describes data and discusses our main findings; in section 5 we provide some additional analysis and robustness checks; section 6 concludes.

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[4] If measured as the difference between the 10-year and 3-month swap rates, as done by Esposito *et al.* (2015), over the 2006-2018 period, the slope of the yield curve first gradually decreased up to the summer of 2008. Then, after Lehman Brothers' failure and the subsequent reduction in monetary policy rates by the ECB, with, for example, the rate on main refinancing operations going down from 3.75% of October 15, 2008, to 1% of December 14, 2011, it recorded a significant increase. Finally, following the European sovereign debt crisis, a new slope reduction was observed.

[5] For further details, visit the following ECB webpage:
https://www.bankingsupervision.europa.eu/press/speeches/date/2022/html/ssm.sp221108~ee0264b638.en.html

2. Literature review

This article contributes to two strands of banking research: first, the studies analyzing the determinants of profitability, particularly those measuring it in terms of net interest margin; second, the research examining the factors affecting interest rate risk exposure. Sections 2.1 and 2.2 review this literature.

2.1 The determinants of bank profitability

The first empirical studies about the determinants on banks' profitability date back to the 1980s. A first group of works has developed and extended the seminal paper by Ho and Saunders (1981). Then, a bunch of papers specifically has investigated the impact of interest rates on bank profits, even by making a distinction between short-term and long-term interest rates, and accounting for the characteristics of the yield curve, particularly in terms of its slope. More recently, literature has been dealing with the effects of banks' interest rate risk exposure and maturity transformation activity, on the one hand, and of unconventional monetary policies, on the other. Empirical results of these two latter streams of studies are mixed and call for further analysis.

Ho and Saunders (1981) describe the bank as a risk-averse intermediary providing liquidity through maturity transformation. If the volumes of loans and deposits, which in their model have the same 1-year maturity, do not match, the bank turns to the money market and becomes exposed to refinancing (reinvestment) risk if loans are larger (smaller) than deposits. They show that major US banks' NIM depends on management's risk aversion, average transactions size, market structure, and interest rate volatility.

The Ho and Saunders (1981) model has been subsequently extended. McShane and Sharpe (1985) identify market interest rate fluctuations as the main source of risk, rather than the uncertainty in loan returns and deposit costs. Angbazo (1997) includes a measure of interest rate risk exposure in the model and considers its interaction with credit risk. Allen (1988) hypothesizes different maturities for loans and deposits and accounts for two types of loans, with interdependent demand functions. Entrop *et al*. (2015) remove the assumption of equal maturities for loans and deposits to explore the extent to which interest risk exposure is priced into bank margins, and conclude that German banks generally price individual interest rate risk via the asset side into the NIM, whereas only small, local banks price interest rate risk via the liability side. Maudos and Fernández de Guevara (2004) explicitly take operating costs into account and use the Lerner index to measure the degree of competition. Carbó Valverde and Rodríguez-Fernàndez (2007) introduce non-traditional activities into the theoretical framework, proposing a multi-output model to analyse the relationship between bank margins and operational specialization. Finally, Maudos and Solís (2009) simultaneously consider operating costs, diversification, and activity specialization, finding a positive relationship between banks' margin and the Lerner index, operating costs, and interest rate volatility, and a negative correlation with management quality and non-interest income.

Interest rates are among the main determinants of bank profitability. Generally, studies report a positive correlation between rates and NIM, interpreting it as a natural consequence of maturity transformation (Flannery, 1981; Hancock, 1985; Bourke, 1989; Saunders and Schumacher, 2000). Some works distinguish between short and long-term rates. According to Albertazzi and Gambacorta (2009), the net interest margin is positively correlated with economic trends and long-term rates, while it is unaffected by short-term rates. Bolt *et al*. (2012) confirm the positive correlation of banks' net interest margin with long-term rates, with an intensity that depends on the economic cycle phase and decreases as the yield curve slope increases; however, short-term rates negatively impact the net interest margin, with an effect that increases with the weight of wholesale funding.

More recently, scholars have focused on the impact of interest rate risk exposure, maturity transformation, and monetary policy on bank profitability. As for the effects of interest rate risk exposure and maturity transformation, Entrop *et al*. (2015) show that interest rate risk exposure and expected returns from maturity transformation contribute to determining German banks' NIM. Bologna (2017) documents that a more intense maturity transformation is associated with higher NIMs for Italian banks, particularly as the yield curve slope increases. Nevertheless, if excessive, maturity transformation might lead to a larger risk exposure without any benefit in terms of NIM.

Regarding the relationship between monetary policy and bank profitability, Alessandri and Nelson (2015) develop a model providing a broad picture of the consequences of a monetary policy shock. By raising short-term rates and flattening the yield curve, a policy tightening typically reduces banks' income. Unconventional monetary policies based on asset purchases are expected to lower income margins to the extent that they succeed in lowering long-term yields. Their empirical analysis is referred to a panel data set containing information on the UK activities of the United Kingdom and foreign banking groups.

Borio *et al*. (2017) prove that short-term interest rates and the slope of the yield curve positively influence the return on assets of an international sample of banks, and document that extremely low interest rates and a flat yield curve erode bank profitability. Conversely, evidence from Altavilla *et al*. (2018) does not indicate any effect on euro area banks' profitability in the years 2000-2016 following a decrease in short-term interest rates and/or a flattening of the yield curve. Claessens *et al*. (2018) observe that a 1 percentage point decrease in interest rates implies an 8 basis point reduction in the NIM of an international sample of banks coming from 47 countries. Furthermore, low rates enhance this effect and, for each additional year, of a "low for long" scenario, NIM and return on assets decrease by an additional 9 and 6 basis points, respectively.

Coulier *et al*. (2023) document that the sensitivity euro area banks' net interest income to changes in interest rates and in the slope of the yield curve depends on the extent of their maturity mismatch: according to their estimates, the NIM raises by 4.8 bps if the 3-month overnight index swap rate experiences a 1% increase, and by 5.8 bps if there is a 1% rise in the yield curve slope. The positive effect of a yield curve steepening on NIMs is larger for banks more engaged in the maturity transformation function. Nevertheless, the authors warn that this might dissipate in the future, especially for banking systems characterized by the prevalence of variable-rate lending.

This paper is close to the works about the impact of interest rate risk and maturity transformation on bank profits and is also linked to the monetary policy related research. Relative to this literature, we contribute first by using a measure of interest rate risk that is compliant with the prudential supervision and that we are able to decompose to account for the exposure stemming from the positions deposits collecting & loans issuing activity, that associated with securities portfolio and the one referred to the derivatives use. Second, to assess the maturity transformation, we use the inverse of the net stable funding ratio, which is something never done before, to the best of our knowledge. Finally, we consider the 2010-2018 period, which allows to examine these relationships under different financial market conditions and to assess the potential impact of unconventional monetary policies.

2.2 The determinants of interest rate risk exposure

It is approximately 40 years that banking scholars devote efforts to study the determinants of banks' vulnerability to interest rates movements. In the '80s of the last century, first papers focused on the analysis of the impact of the maturity mismatch between assets and liabilities and adopted a market-based approach to measure banks' riskiness, which was particularly assessed through the sensitivity of stock returns to changes in interest rates. Successive works have progressively extended the list of potential factors affecting interest rate risk exposure, by accounting for a number of bank-specific characteristics, mainly related to the composition of the asset and liability sides of the balance sheet, such as equity endowment and loan and deposit volumes, and to the peculiarities of the profit and loss account, considering for example the share of non-interest income over total revenues and loan loss provisions set aside to cover credit risk. Finally, the protracted scenario of extremely low, and even negative, interest rates caused by the ultra-expansionary monetary policies adopted in response to the global financial crisis, earlier, and to the euro area sovereign debt crisis, later, has incentivised researchers to investigate the impact of both these extra-ordinary conditions and the consequences of the normalization process started in July 2022.

In 1984, Flannery and James show that the mismatch of asset and liability maturities could explain the different sensitivity of banks to interest rates fluctuations. Subsequent works by Yourougou (1990), Kwan (1991), and Akella and Greenbaum (1992) support this thesis and several empirical studies extended the analysis by incorporating the effect of derivative usage on banks' interest rate risk (Hirtle, 1997; Schrand, 1997; Zhao and Moser, 2006). Some authors focus on the correlation of banks' interest rate risk exposure with a range of specific bank characteristics. Drakos (2001) shows that working capital is the main source of Greek banks' sensitivity to interest rate changes, a significant portion of which also depends on market value, equity, and debt. Fraser *et al*. (2002) prove that US banks' interest rate risk exposure is negatively (positively) correlated with the amount of equity, sight deposits, and loans. The correlation is positive with the share of non-interest revenues, probably because an increase in the incidence of such revenues is associated with a greater involvement in securities-related activities, such as underwriting and advisory. Saporoschenko (2002) finds that Japanese banks' interest rate risk exposure is positively correlated with bank size and deposit volume, while the maturity gap does not seem to have a significant impact.

Reichert and Shyu (2003) show that the use of options tends to increase interest rate risk exposure of US, European and Japanese large international banks, whereas both interest rate and currency swaps generally reduce it. Equity endowment, commercial loans, liquidity level, and loan loss provisions have a significant impact on interest rate risk exposure, although not entirely consistent among the three geographical areas. Based on the analysis of Asia-Pacific banks, Au Yong *et al*. (2007) suggest that the level of derivatives activity is positively associated with long-term interest rate exposure but negatively with short-term interest rate exposure.

Unlike the studies discussed above, Esposito *et al*. (2015) measure the exposure to the interest rate risk using the BCBS' duration gap approach. They show that Italian banks have limited interest rate risk exposure and manage it using changes in balance sheet exposure and interest rate derivatives as substitutes, with a substantial heterogeneity in risk management practices. Smaller banks and those with a greater commitment to traditional banking follow an integrated approach to managing interest rate and credit risk. Most of their sample banks tend to value gains from interest rate increases even in the face of widening funding gaps.

By analysing the interest rate risk exposure of Eurozone listed banks under the ECB's supervision Foos *et al*. (2017) assess the sensitivity of bank stock prices to changes in level, slope, and curvature of the yield curve. This sensitivity depends on bank-specific characteristics: larger intermediaries, with higher capital coefficients, and larger (smaller) customer loans (deposits) shares, are particularly sensitive to interest rate changes. Chaudron (2018) studies changes in interest rate risk exposure over time and how asset returns and interest margins depend on income from maturity transformation for a sample of Dutch banks, under a scenario of falling rates and flattening yield curve. Interest rate risk exposure is negatively correlated with financial leverage, shows a U-shaped relationship with solvency, does not systematically vary with bank size, and is higher for banks that received public assistance during the global financial crisis.

Hoffmann *et al*. (2019) analyse a sample of banks directly supervised by the ECB and find that for half of these intermediaries an increase in interest rates leads to higher net worth and income. Variation in risk exposure seems to be greater across countries than across bank business models. Particularly, by examining two groups of countries, i.e., those where fixed rates prevail and those where rates are mostly variable, they find that banks with a larger share of retail loans drive the observed variation. Molyneaux *et al*. (2020) identify specific bank characteristics that may amplify or weaken the impact of an interest rate hike on 81 Eurozone banks. Banks with a higher share of variable interest rate loans and a diversified loan portfolio, both by sector and geographical area, are less exposed to rising interest rates.

We add to this literature by specifically investigating whether and how deposits at and, especially, funds borrowed from the ECB contribute to determine banks' exposure to interest rate risk. In this perspective, we again take advantage of the sample period we are interested in. In the years 2010-2018 banks had to face unprecedented financial market conditions, which were shaped by the ECB's ultra-expansionary monetary policy measures, namely the NIRP, which was introduced in June 2014, and the LTROs and TLROs, through which the euro area monetary authority aimed to ensure banks' support to the real economy by providing them with stable and extremely competitive funding sources.

Thus, we not only detect the contribution of factors never considered by prior studies, but we also can test some of the relationships traditionally investigated by previous works under conditions never experienced before.

3. Empirical analysis

3.1 Methodology

The study of the impact of maturity transformation, interest rate risk exposure and the other micro and macro determinants on banks' net interest margin is conducted through the following linear regression model in equation (1):

$$NIM_{it} = c + \sum_{j=1}^{J} \beta_j X_{it}^{j} + \sum_{m=1}^{M} \beta_m X_t^{m} + \varepsilon_{it} \qquad \varepsilon_{it} = v_i + u_{it} \qquad (1)$$

where:

- NIM_{it} is the measure of bank profitability, i.e., the ratio of the net interest margin over total assets of the *i-th* bank at time *t*, with *i = 1, ..., N* and *t = 1, ..., T* years;
- *c* is a constant;
- X_{it}^{j} are bank-specific variables, among which the two main variables, respectively measuring the interest rate risk exposure and the intensity of maturity transformation, plus some other control variables;
- X_t^{m} are macroeconomic control variables;
- ε_{it} is the error term, with a bank-specific component v_i and an idiosyncratic factor u_{it}.

To detect the determinants of our sample banks' interest rate risk exposure, we employ the linear regression model of the following equation (2):

$$IRRBB_{it} = c + \sum_{j=1}^{J} \beta_j \Phi_{it}^{j} + \sum_{m=1}^{M} \beta_m \Phi_t^{m} + \varepsilon_{it} \qquad \varepsilon_{it} = v_i + u_{it} \qquad (2)$$

where:

- $IRRBB_{it}$ is the measure of the exposure to interest rate risk in the banking book of the *i-th* bank at time *t*, with *i = 1, ..., N* and *t = 1, ..., T* years;
- *c* is a constant;
- Φ_{it}^{j} are bank-specific variables, among which three main variables, respectively measuring the intensity of maturity transformation, loans from the ECB and deposits at the ECB, plus some other control variables;
- Φ_t^{m} are macroeconomic control variables;
- ε_{it} is the error term, with a bank-specific component v_i and an idiosyncratic factor u_{it}.

All the variables, both main and control variables are described in the following section 3.2 and presented in Table 1. Following Bologna (2017) for the NIM determinants, and Entrop *et al*. (2015) for the IRRBB analysis, models in equations (1) and (2) are estimated using the Generalized Method of Moments (GMM) proposed by Blundell and Bond (1998), widely used in the literature to estimate a dynamic panel equation with a relatively small time dimension and a larger number of units, i.e., with small T and large N. The approach accounts for endogeneity, controls for unobserved heterogeneity, and handles biases and inconsistencies typical of OLS estimates, provided there is no second-order serial correlation and the instruments used are valid. Consistent with Bologna (2017), bank size is considered a predetermined variable, all other bank-specific variables are treated as endogenous, and macroeconomic variables are treated as exogenous. We instrument for all the bank-specific regressors but bank size; we apply the instruments to the level equation and, to limit their proliferation, we cap to two the number of lags of the endogenous variables used as instruments.

To assess the impact of unconventional monetary policy measures on the relationships between bank profitability and interest rate risk exposure with their respective determinants, each model is estimated for two sets of years of the entire investigation period. The first includes the years ranging from 2006 to 2011, when the ECB still had to introduce such measures; the second goes from 2012 to 2018, when the long-term refinancing operations, the targeted targeted long-term refinancing operations and the negative interest rate policy were all at work.

3.2 Variables

3.2.1 Variables of interest and hypotheses development

The ratio of net interest margin to total assets (NIM) is our measure of bank profitability and is the dependent variable of the model in equation (1), where banks' exposure to the interest rate risk (IRRBB) and the proxy for their maturity transformation (MT) are the main independent variables. As for the IRRBB variable, our banks' exposure to interest rate risk has been calculated using the economic value approach adopted by the prudential supervision and considering a +200 bp parallel shock in interest rates. Assets and liabilities have been allotted into the time bands of the regulatory maturity ladder based on their residual maturity or repricing date. For each time band, the difference between assets and liabilities, i.e., the so-called net position, is calculated and then weighted by the product of an average modified duration coefficient and the interest rate shock. Summing up the weighted net positions of all the time bands and dividing this sum by a measure of regulatory capital yields a risk indicator, a positive (negative) value of which signals a decrease (increase) in the overall bank economic value. A positive value of the risk indicator means a reduction in the bank economic value as a percentage of its regulatory capital.

Data required for the IRRBB estimation has been hand collected from our sample banks' balance sheet. From this perspective, this study is close to Chaudron (2018) and Esposito *et al*. (2015), who respectively use Dutch and Italian national supervisory data. Compared with previous studies, this allows us a much greater detail about banks' exposure, of which we take advantage in the analysis of profitability determinants. Our data collection and analysis allow to break the overall risk indicator down into three components, whose incidence on banks' NIM has never been investigated before.

Particularly, these three components are defined as follows: first, the "banking exposure" (IRRBB_B), given by the part of the total IRRBB exposure stemming from traditional and direct borrowing and lending activities, mainly consisting in deposits and loans; second, the "securities exposure" (IRRBB_S), which is the contribution of our banks' securities portfolio to the overall exposure, and third the "derivatives exposure" (IRRBB_D), which is related to banks' positions on derivative financial products. Again, as for the overall risk indicator, positive values of the risk indexes referred to these components mean a raise in the bank exposure to interest rate risk.

In line with prior literature (Angbazo, 1997; Saunders and Schumacher, 2000; Maudos and Fernández de Guevara, 2004; Entrop *et al*., 2015), the exposure to the interest rate risk is expected to be positively associated with the net interest margin, thus implying a positive expected sign for the coefficient of the variable IRRBB. Our first research hypothesis, concerning the impact of banks' exposure to interest rate risk and their profitability, can be therefore stated as follows:

H1: Banks' exposure to interest rate risk in the banking book positively affects net interest margin.

Data constraints do not allow to consider the contractual maturity of our banks' assets and liabilities to measure the proxy for the maturity transformation activity, as done by Bologna (2017) and Esposito *et al*. (2015), who respectively estimate maturity transformation as the duration of assets and liabilities and as a function of the contractual remaining time to maturity. Following Casu *et al*. (2018), the intensity of maturity transformation is first measured by the inverse of the net stable funding ratio introduced by the Basel III reform of the international prudential supervision after the 2007-2008 global financial crisis. So, put in terms of liquidity regulation, the first proxy for the maturity transformation, labelled MT1, is the ratio of required stable funding to available stable funding. Consistent with previous studies (e.g., Bologna, 2017), within the robustness checks section, we replace MT1 with the ratio of the loans granted to over the deposits collected from retail customers (MT2). In line with prior literature (Bologna, 2017; Foos *et al*., 2017), both MT1 and MT2 are expected to have a positive impact on net interest margin, on the one hand, and on interest rate risk, on the other, thus implying positive regression coefficients in both equations (1) and (2). Our second hypothesis, referred to the relationship between maturity transformation and profitability can be stated as follows:

H2: Banks' maturity transformation positively affects net interest margin.

The IRRBB variable becomes the dependent variable of equation (2), where we analyse the determinants of banks' exposure to the interest rate risk in the banking book. Relative to prior literature, the impact of the monetary policy measures implemented by the ECB in the second part of the sample period is assessed through the exam of the relationships between IRRBB, on the one hand, and loans from and deposits at the ECB, on the other hand. Specifically, two items of sample banks' balance sheets are considered: "Cash and cash equivalents" on the asset side, which includes deposits at the ECB and "Liabilities to banks" on the liability side, which contains the funds that banks receive from the ECB. The ratios of these two items to total assets are labelled LAB and DFB.

As far as the expected signs of their regression coefficients, we argue that, since the use of funding from the ECB through (targeted) long-term refinancing operations has allowed banks to stabilize their liabilities, as in the intentions of the ECB itself,[6] their presence in intermediaries' funding mix should reduce these latter exposure to upward interest rate fluctuations, which entails that the expected sign of the DFB regression coefficient is negative. In this sense, even if they use a different measure for the exposure to the interest rate risk, our expectation is in line with Molyneux *et al*. (2022), who highlights the positive effects of TLTROs in terms of reduced and diversified funding costs. As for the variable LAB, an increase of which contributes to make more liquid the overall assets side of a bank involved in the traditional intermediation activity, with a large share of long-term loans on the asset side, we expect a negative sign for the LAB regression coefficient. The final two hypotheses tested in the empirical analysis, about the relationship between LAB and DFB, on the one hand, and IRRBB, on the other, can be stated as follows:

H3: Banks' funds from the ECB reduce the exposure to the interest rate risk.

H4: Banks' deposits at the ECB reduce the exposure to the interest rate risk.

3.2.2 Control variables

In our analysis of the determinants of net interest margin and interest rate risk exposure we use two groups of control variables: a first set consists of bank-specific indices, respectively measuring bank size, credit risk exposure and overall risk aversion. The second set of regressors includes macroeconomic variables, namely the level of interest rates, the slope of the yield curve, and the state of the Italian economy.

Bank-specific variables

The variable used to account for the size of the bank (SIZE) is given by the natural logarithm of total assets. Empirical investigations show conflicting results regarding its impact on net interest margin: Albertazzi and Gambacorta (2009) and Ho and Saunders (1981) observe that NIM increases with bank size, while Fungáčová and Poghosyan (2011) and Maudos and Fernández de Guevara (2004) find a negative relationship between the two variables. Therefore, we do expect either a positive or a negative sign for the regression coefficient of the SIZE variable in equation (1). Its impact on the exposure to interest rate risk is expected to be positive, with a positive regression coefficient in equation (2). Consistent with a moral hazard interpretation of the relationship between

[6] https://www.ecb.europa.eu/ecb-and-you/explainers/tell-me/html/tltro.en.html

size and risk variables, we expect a reduction in risk aversion as bank size increases, due to the increased probability that banks are perceived as "too big to fail".

Credit risk exposure (CR) is measured by the ratio of non-performing loans to total assets. According to most of previous studies, an increase in credit risk should result in a corresponding increase in net interest margin due to the higher risk premium required by banks (Angbazo, 1997; Maudos and Fernández de Guevara, 2004). However, since some works highlight a negative relationship (e.g., Williams, 2007), we do not take any a priori position on the expected sign of the regression coefficient for this variable in equation (1). In the analysis of the determinants of interest rate risk exposure in equation (2), on the other hand, a negative relationship is expected in line with prior literature (e.g., Foos *et al*., 2017).

Risk aversion (RA) is often assessed through indicators of capital adequacy typical of prudential supervisory practices or through traditional leverage ratios. Consistent with Bologna (2017), risk aversion is here measured by the capital in excess to the required minimum to total risk-weighted assets, i.e., the difference between the total capital ratio and the minimum threshold of 8%. The literature presents conflicting results on the relationship between bank net interest margin and the degree of risk aversion, even if most of studies highlight a positive relationship (Angbazo, 1997; Fernández de Guevara, 2004; Maudos and Solís, 2009; Bologna, 2017), justified by the demand from intermediaries for higher margins to compensate for the opportunity cost arising from the greater allocation of own funds withdrawn from the income-generating circuit of productive investments. Entrop *et al*. (2015) use the ratio of excess capital over regulatory minimums to total assets to estimate bank risk aversion and confirm the positive correlation between this measure and net interest margin. By reducing banks' riskiness, greater capital endowment could lead to a reduction in the cost of funding, resulting in an increase in net interest margin. Nevertheless, prudent management could lead not only to higher capitalization but also to extremely conservative lending policies, which, because of the lower interest income, would justify a negative relationship between capitalization and NIM. In line with the majority of previous studies, we expect a positive regression coefficient for the RA variable in equation (1).

The ex-ante analysis of the impact of our measure of risk aversion on the IRRBB variable in equation (2) is not straightforward as well, and previous literature does not help because banks' exposure to interest rate risk is mainly given by market-based sensitivity measures. Since higher solvency, expressed by a wider endowment of own funds compared to the minimum required threshold, allows the bank to assume more risk, the expected sign of the relationship between the RA and IRRBB might be positive. On the other hand, a higher capital endowment reduces the leverage and make the liability side more stable, thus reducing IRRBB coeteris paribus. In the light of that, the expected sign of the regression coefficient of the RA variable in equation (2) might be either positive or negative.

Macroeconomic variables

As far as macroeconomic control variables are concerned, previous studies have included interest rate volatility, the level and slope of the yield curve. Consistent with Esposito *et al*. (2015), in the first specification of the profitability model described in equation (1), temporal dummies are used (see columns 1 in both panels of Table 4). These dummies not only capture the effect of macroeconomic conditions, which are invariant for banks but vary over time, but also help to mitigate endogeneity issues due to the presence of variables whose behaviour may be driven by common macroeconomic factors. In two subsequent specifications (see columns 2 and 3 in both panels of Table 4), macroeconomic control variables are used, such as the growth rate of gross domestic product (GDPGR), the level of short-term interest rate, given by the three-month Euribor (EUR3M), and the slope of the yield curve (SLOPE), calculated as the difference between the 10-year IRS swap rate and the three-month Euribor. Consistently with previous research, all these variables are expected to have a positive relationship with bank net interest margin in equation (1).

Following Grove (1974) and Prisman and Tian (1993), we assume that it is the yield spread rather than the level of interest rates that impacts interest rate risk exposure: therefore, the regression coefficient of the EUR3M variable is expected to be non-significant in equation (2). The spread between long-term and short-term rates (SLOPE) is an indicator of future changes in long-term rates (Campbell and Shiller, 1991) and can be interpreted as a measure of banks' ability to "exploit" the yield curve by employing a borrow short and lend long strategy.

An increase in the slope of the yield curve should correspond to an increase in interest rate risk exposure, thus suggesting a positive regression coefficient for the SLOPE variable in equation (2). We do not have any a priori about the relationship of the state of the economy, as measured by the GDP growth rate, and banks' exposure to interest rate risk, since previous literature does not typically use this control.

Table 1: Variables

	Variable	***Symbol***	***Description***	***Source***
Bank specific variables				
Net interest margin (dependent variable in eq. 1)	$\frac{\text{Net interest margin}}{\text{Total assets}}$	NIM_{it}	Ratio of net interest margin to total assets	BF
Interest rate risk in the banking book (dependent variable in eq. 2)	IRRBB	$IRRBB_{it}$	BCBS risk indicator based on a +200 bp shock.	BS
Interest rate risk from banking activity	IRRBB_B	$IRRBB\_B_{it}$	Share of IRRBB exposure stemming from deposit collection and loans issuing activity	BS
Interest rate risk from securities portfolio	IRRBB_S	$IRRBB\_S_{it}$	Share of IRRBB exposure stemming from securities portfolio	BS

Interest rate risk from derivatives	IRRBB_D	$IRRBB\_D_{it}$	Share of IRRBB exposure stemming from derivative positions	BS
Credit risk	$\frac{\text{Non}-\text{performing loans}}{\text{Total assets}}$	CR_{it}	Ratio of non performing loans to total assets	BF
Maturity transformation	$\frac{1}{\text{Net Stable Funding Ratio}}$	$MT1_{it}$	Inverse of Net Stable Funding Ratio	BF
	$\frac{\text{Customer loans}}{\text{Customer deposits}}$	$MT2_{it}$	Ratio of customer loans to customer deposits	BF
Risk aversion	$\text{Total Capital Ratio} - 8\%$	RA_{it}	Difference between total capital ratio and 8%	BF
Bank size	Ln(Total assets)	$SIZE_{it}$	Natura logarithm of total assets (in € thousands)	BF
Deposits at the ECB	$\frac{\text{Deposits at the ECB}}{\text{Total assets}}$	LAB_{it}	Ratio of deposits at the ECB to total assets	BF+BS
Funding from the ECB	$\frac{\text{Debt towards ECB}}{\text{Total assets}}$	DFB_{it}	Ratio of debt towards ECB to total assets	BF+BS
Macroeconomic variables				
GDP annual growth rate	$\frac{\text{GDP}_t - \text{GDP}_{t-1}}{\text{GDP}_{t-1}}$	$GDPGR_t$	Annual GDP growth rate (in percentage)	EU
Short-term interest rate level	3-month Euribor	$EUR3M_t$	Average annual 3-month Euribor (in percentage)	REF
Yield curve slope	Spread between long-term interest rate and short-term interest rate	$SLOPE_t$	Difference between 10-year IRS rate and 3-month Euribor (in percentage)	REF

Note: BF = Moody's Analytics Bank-Focus; BS: Bank balance sheets; EU = Eurostat; REF = Refinitiv Datastream

4. Data and results

4.1 Data

We examine a sample of 125 unlisted Italian banks, active at a provincial or regional level, over the period ranging from 2006 to 2018 with annual observations. The sample includes 106 limited liability cooperative banks, of which, according to the Italian banking law, 90 are "*banche di credito cooperativo*" and 16 are "*banche popolari*", with the remaining 19 having a joint-stock company legal form ("*società per azioni*"). We refer to the "*banche di credito cooperativo*" and "*banche popolari*" generally as "*cooperative banks*", and to the joint-stock banks as "*joint-stock banks*".

Data regarding banking variables is taken from the Moody's Analytics Bank-Focus database, except for interest rate risk exposure, which is calculated based on data collected from our sample banks' balance sheets. To avoid double counting, our data is drawn from the consolidated balance sheets, if available, or from the unconsolidated financial statements, otherwise. Data related to the level of the three-month Euribor and the slope of the yield curve is obtained from the Refinitiv Datastream database, while the annual growth rate of the Italian gross domestic product is computed based on data from Eurostat.

Table 2A shows the main descriptive statistics of the variables for the whole sample, whereas Table 2B reports those referred to the cooperative banks (Panel A) and commercial banks (Panel B) sub-samples, as well as the results of the tests run for the statistical significance of the differences between the means (Panel C). Overall, our sample banks are heavily engaged in traditional credit intermediation activities: the average values of the ratio of loans to customers to total assets and the ratio of customer deposits to total assets are 69.09% and 51.72%, respectively (data not shown here). The ratio of loans to customers to total assets is 69.14% for the sub-sample of cooperative banks and 68.30% for joint-stock banks; customer deposits are 51.33% of cooperative banks' total assets and 58.40% of joint-stock banks' total assets.

Table 2A shows that the average value of the net interest margin to total assets ratio (NIM) is 2.2%, and the ratio of non-performing loans to total assets (CR) is 7.7%. As for the overall interest rate risk exposure (IRRBB), in the case of a parallel shift upward of the yield curve by 200 basis points, our sample banks experience a reduction in their economic value averaging 1.7% of the regulatory capital during the years 2006-2018. On average, a 200-basis point increase in the yield curve leads to a raise in our banks' economic value, if we focus on the component of the interest rate risk exposure stemming from the traditional loans-deposits intermediation activity (IRRBB_B is -8.2%), and to a reduction of their economic value, if we look at the interest rate risk exposure stemming from banks' positions in securities (IRRBB_S is 6.9%) and derivatives (IRRBB_D equals 2.1%).

Our sample banks comply with the requirement imposed by the prudential supervisory framework in terms of the NSFR: MT1, which is its inverse, has an average value of 0.909. In terms of risk aversion (RA), banks in the sample have an average regulatory capital surplus to the minimum capital requirement of 8%, amounting to approximately 7.8%, implying an average total capital ratio over the period of about 15.8%. Regarding the variables measuring the transitions with the ECB, the average values of the ratio of deposits at the ECB to total assets (LAB) and the ratio of funding from the euro area monetary authority to total assets (DFB) are 6% and 9.4%, respectively. The evolution over the years 2006-2018 of these two variables is depicted in Figure 1, which reports a significant increase in DFB due to the launch of the first LTROs in December 2011 and January 2012, followed by two series of TLTROs of 2014 and 2016.

Table 2A: Descriptive statistics: whole sample for the years 2006-2018

	Mean	Std. Dev.	Median
NIM	0.022	0.007	0.021
IRRBB	0.017	0.119	0.000
IRRBB_B	-0.082	0.104	-0.087
IRRBB_S	0.069	0.123	0.022
IRRBB_D	0.021	0.051	0.004
CR	0.077	0.049	0.067
MT1	0.909	0.141	0.882
RA	7.789	5.208	6.742
SIZE	13.724	1.123	0.078
DFB	0.094	0.088	0.049
LAB	0.060	0.043	13.606
GDPGR	-0.080	2.101	0.774
EUR3M	1.266	1.667	0.573
SLOPE	1.654	0.912	1.302

Note: For the definition of the variables, please refer to the previous Table 1

Figure 1A: Deposits at (LAB) and funding from (DFB) the ECB: whole sample for the years 2006-2018

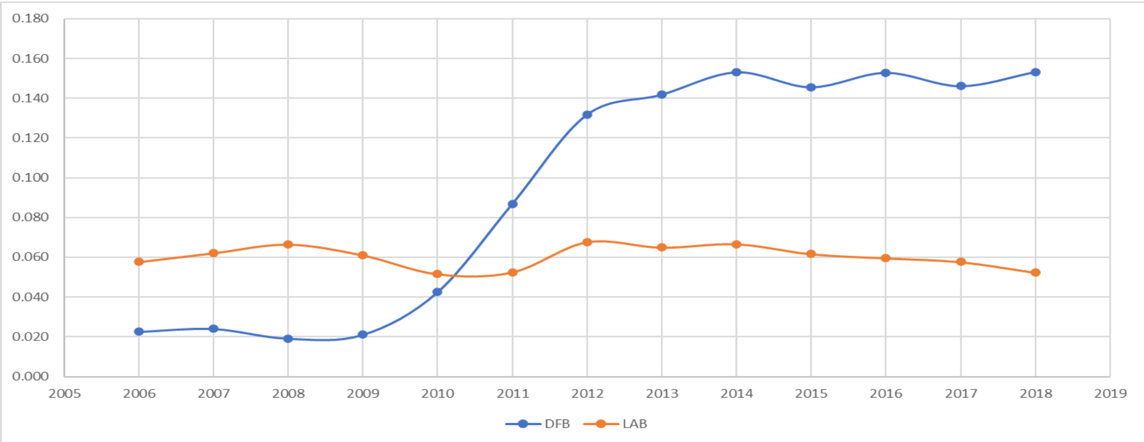


Table 2B reports that cooperative and joint-stock banks have approximately an equal ratio of net interest margin to total assets (2.2% for cooperative banks and 2.1% for joint-stock intermediaries), even if the very small difference appears statistically significant at the 1% confidence level. Cooperative banks seem to be more risk adverse than joint-stock institutions (the mean value of the variable RA is 8.001% for the former and 4.043% for the latter, with a difference statistically significant at the 1% confidence level). Joint-stock banks are on average larger than cooperative ones (the mean of the natural logarithm of their total assets is 14.950 vs. 13.651 for cooperative intermediaries), again with a difference which is statistically significant at the 1% confidence level. Cooperative banks seem to be slightly less involved in maturity transformation activity, being characterized by a 0.908 value for the MT1 variable, smaller than the 0.921 value of the joint-stock institutions.

While cooperative banks are exposed to a 200-bp raise in interest rates (IRRBB is 1.9%), joint-stock institutions would experience a decline in their economic value following a decrease in interest rates (IRRBB equals -2.2%), with a difference statistically significant at the 1% confidence level. No statistically significant difference is found for the exposure stemming from loans-deposits intermediation activity: IRRBB_B stands at 8.2% for cooperative banks and at 7.9% for joint-stock ones. As concerns both the securities portfolio and derivatives positions, cooperative banks are more exposed to a raise in interest rates than joint-stocks intermediaries: IRRBB_S and IRRBB_D are 7.1% and 2.2%, respectively, for the former, and 4.3% and 0.5%, respectively, for the latter, with mean differences statistically significant at the 1% confidence level for both securities and derivatives positions.

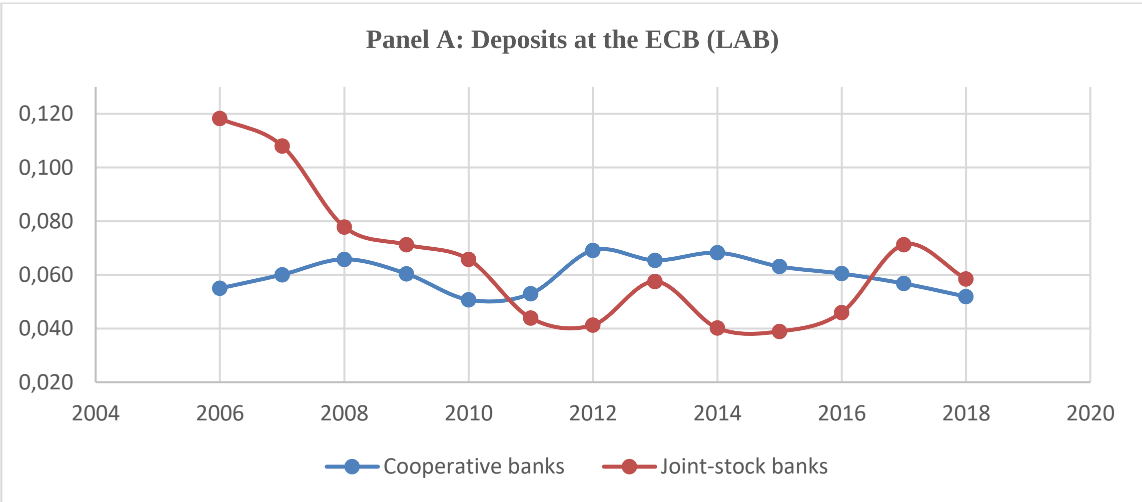
Figure 1B separately shows for cooperative and joint-stock banks the trend in the deposits at the ECB (Panel A) and the funding coming from the euro area monetary authority (Panel B) over the years 2006-2018. Joint-stock banks show a marked decline in the deposits they have at the ECB: the variable LAB goes from 11.82% in 2006 to 5.85% in 2016, whereas the trend for the cooperative banks seems to be quite flat. Both groups of banks experience a steep increase in the share of deposits from the ECB to total assets (DFB), which starts from a value of 2.91% and 2.22% for joint-stock and for cooperative banks in 2006 and gets to 18.43% and 15.11%, respectively, in 2018.

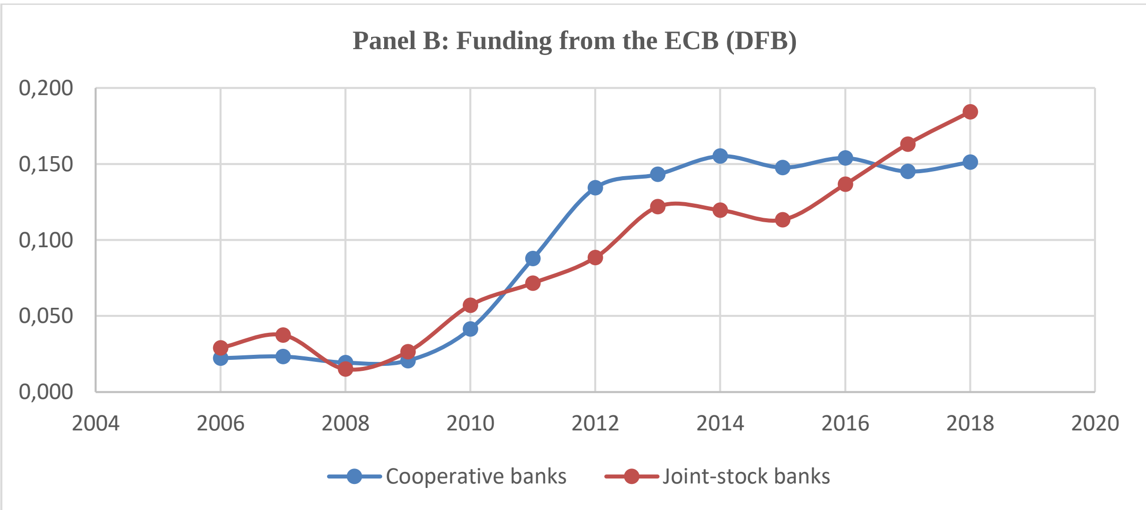
Table 2B: Descriptive statistics: cooperative banks vs. joint-stock banks for the years 2006-2018

	Panel A: Cooperative banks			Panel B: Joint-stock banks			Panel C: Difference in means (cooperative banks vs. joint-stock banks)
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	
NIM	0.022	0.007	0.021	0.019	0.006	0.018	0.004***
IRRBB	0.019	0.118	0.000	-0.022	0.131	-0.016	0.041***
IRRBB_B	-0.082	0.104	-0.087	-0.079	0.109	-0.070	0.002
IRRBB_S	0.071	0.123	0.023	0.043	0.121	0.007	0.028**
IRRBB_D	0.022	0.050	0.005	0.005	0.061	0.000	0.017**
CR	0.077	0.048	0.068	0.071	0.070	0.047	0.006
MT1	0.908	0.140	0.882	0.921	0.166	0.890	-0.013
RA	8.001	5.251	6.970	4.043	2.067	4.110	3.957***
SIZE	13.651	1.058	13.564	14.950	1.455	14.655	-1.299***
DFB	0.094	0.087	0.080	0.091	0.104	0.061	0.003
LAB	0.060	0.042	0.050	0.062	0.057	0.044	-0.002

Notes: For the definition of the variables, please refer to the previous Table 1. **, *** indicate statistically significant correlation coefficients at the 5% and 1% levels.

Figure 2B: Deposits at the ECB (LAB) (Panel A) and funding from the ECB (DFB) (Panel B): cooperative banks vs. joint-stock banks for the years 2006-2018





Note: For the definition of the variables, please refer to the previous Table 1.

Table 3A shows the pairwise correlation coefficients among the variables under investigation in our empirical analysis for the whole sample over the years 2006-2018, whereas Panel A and Panel B of Table 3B do the same for the sample of cooperative and joint-stock banks, respectively.

Table 3A shows that NIM and IRRBB are inversely correlated with each other and respectively exhibit negative and positive correlations with the measures of credit risk exposure (CR), the intensity of maturity transformation activity (MIT1), and funding from the ECB (DFB).

The level of interest rates (EUR3M) and the slope of the yield curve (SLOPE) are positively correlated with the ratio of net interest margin to total assets and negatively correlated with interest rate risk exposure.

For both NIM and IRRBB, the correlation coefficient with the proxy measuring banks' risk aversion (RA) is positive. Table 3B confirms these results for the two groups of banks we have in our sample, with the only exception of the correlation coefficients of RA with NIM and IRRBB for the joint-stock banks, which are negative and positive, respectively, even if only marginally significant at the 10% confidence level.

Table 3A: Pairwise correlation coefficients: whole sample for the years 2006-2018

	NIM	IRRBB	CR	MT1	RA	SIZE	DFB	LAB	GDPGR	EUR3M	SLOPE
NIM	1										
IRRBB	-0.12***	1									
CR	-0.45***	0.19***	1								
MT1	-0.31***	0.33***	0.46*	1							
RA	0.10***	0.21***	-0.09***	-0.14***	1						
SIZE	-0.32***	-0.03	0.09***	0.26***	-0.28***	1					
DFB	-0.41***	0.39***	0.38***	0.72***	0.13***	0.16***	1				
LAB	0.04*	0.00	-0.07***	-0.26***	0.17***	-0.27***	0.07**	1			
GDPGR	-0.09***	0.03	0.08***	0.14***	0.05**	0.01	0.08***	-0.06**	1		
EUR3M	0.55***	-0.32***	-0.54***	-0.48***	-0.10***	-0.17***	-0.54***	0.03	0.03	1	
SLOPE	0.27***	-0.16***	-0.15***	-0.07***	-0.06	-0.01	-0.19***	-0.03	-0.56***	-0.12***	1

Notes: For the definition of the variables, please refer to the previous Table 1. *, **, *** indicate statistically significant correlation coefficients at the 10%, 5% and 1% levels.

Table 3B: Pairwise correlation coefficients: cooperative banks vs. joint-stock banks for the years 2006-2018

Panel A: Cooperative banks

	NIM	IRRBB	CR	MT1	RA	SIZE	DFB	LAB	GDPGR	EUR3M	SLOPE
NIM	1										
IRRBB	-0.20***	1									
CR	-0.43***	0.18***	1								
MT1	-0.48***	0.31***	0.45***	1							
RA	0.11***	0.20***	-0.10***	-0.15***	1						
SIZE	-0.42***	-0.02	0.09***	0.28***	-0.26***	1					
DFB	-0.56***	0.37***	0.39***	0.71***	0.13***	0.20***	1				
LAB	0.10***	0.02	-0.06**	-0.26***	0.19***	-0.27***	0.07***	1			
GDPGR	-0.05*	0.02	0.08***	0.14***	0.05*	0.01	0.07***	-0.07***	1		
EUR3M	0.76***	-0.32***	-0.56***	-0.48***	-0.11***	-0.18***	-0.56***	0.01	0.03	1	
SLOPE	0.02	-0.15***	-0.15***	-0.06**	-0.05*	-0.01	-0.19***	-0.03	-0.56***	-0.12***	1

Panel B: Joint-stock banks

	NIM	IRRBB	CR	MT1	RA	SIZE	DFB	LAB	GDPGR	EUR3M	SLOPE
NIM	1										
IRRBB	-0.36***	1									
CR	-0.33***	0.28**	1								
MT1	-0.40***	0.66***	0.59***	1							
RA	-0.20*	0.22*	-0.05	0.08	1						
SIZE	0.06	0.10	0.27**	0.06	-0.15	1					
DFB	-0.46***	0.68***	0.32***	0.86***	0.23**	-0.17	1				
LAB	0.00	-0.20*	-0.21*	-0.28**	-0.01	-0.43***	0.02	1			
GDPGR	-0.13	0.07	0.11	0.10	0.20*	0.03	0.15	0.06	1		
EUR3M	0.64***	-0.31***	-0.41***	-0.50***	-0.43***	0.04	-0.41***	0.28***	-0.02	1	
SLOPE	0.13	-0.34***	-0.20*	-0.16	-0.30***	-0.11	-0.19*	-0.07	-0.54***	-0.04	1

Note: For the definition of the variables, please refer to the previous Table 1. *, **, *** indicate statistically significant correlation coefficients at the 10%, 5% and 1% levels.

4.2 Results

4.2.1 The determinants of the net interest margin

Table 4 shows the results of the model in equation (1) applied to the whole sample of banks. Panel A refers to the years ranging from 2006 to 2011, whereas Panel B contains the estimates obtained for the period 2012-2018. For each panel, specifications (1) and (2) both include the overall measure of banks' exposure to interest rate risk (IRRBB); specification (2) also accounts for macroeconomic and financial variables, namely the Italian GDP growth rate (GDPGR), interest rate level (EUR3M), and yield curve slope (SLOPE). In specification (3), we replace the overall interest rate risk indicator with its three components, respectively measuring the exposure stemming from traditional activity of deposits collecting and loans issuing (IRRBB_B), the risk from securities held in their portfolio (IRRBB_S), and that from their positions in financial derivatives (IRRBB_D).

At the bottom of the table, we report the statistics and the corresponding p-values of the Arellano Bond test for autocorrelation and of the Sargan test of overidentifying restrictions (Arellano and Bond, 1991). The AR(2) tests confirm that the model is not subject to serial correlation issues. Specifically, the AR tests reject the hypothesis of second-order serial correlation, which is satisfactory as both the first and second lags of endogenous variables are utilized as instruments for their current values. The results of the Sargan test support the validity of the instruments used in the estimation.

The autoregressive component of the net interest margin to total assets ratio ($NIM_{i,t-1}$) is significant in explaining the level of the same variable in time *t*, both statistically and economically, except for specification (1) for the period 2006-2011, where, though significant at the 1% confidence level, the coefficient is approximately four times smaller than those of the other specifications. Overall, bank size (SIZE), credit risk exposure (CR) and risk aversion (RA) are significantly associated with the NIM. *Ceteris paribus*, banks' net interest margin appears to be larger for smaller banks, for intermediaries less exposed to credit risk and less risk adverse.

The evidence regarding the relationship between credit risk and net interest margin contradicts the prevailing literature but is in line with the hypothesis that banks might be willing to grant loans to lower credit-quality borrowers to increase their market share. The negative coefficient of the size variable is in line with previous studies and suggests that the larger is the bank, the lower is the net interest margin, which might be consistent with their objective to develop a broader and broader client base. Banks' risk aversion seems to exert a limited impact on their net interest margin, given the size of the regression coefficients of the RA variable.

The GDP growth rate and yield curve slope are positively correlated with net interest margin, as expected. However, the level of interest rates, proxied by the three-month Euribor rate, exhibits a change in the sign of the coefficient between the two sub-periods: net interest margin increases with rising interest rates in the years 2006-2011, while it experiences a decrease over the 2012-2018 period. To further investigate this aspect, the model was adjusted by adding independent variables representing changes in interest rates (D.EUR3M) and yield curve slope (D.SLOPE), which can be interpreted as short-term effects of interest rate changes.

The negative coefficients of these additional variables suggest significant frictions in the repricing of assets and liabilities, particularly in the second period, where unexpected increases in interest rates may compress bank net interest margin in the short-term. These frictions seem to persist even in the long term, with higher interest rates and a steeper yield curve potentially leading to a reduction in net interest margin.

Minor differences between the two periods are also observed in terms of interest rate risk exposure (IRRBB), although the coefficient remains positive in both groups of years, thus providing an overall support to our H1 hypothesis. By comparing the regression coefficients of the variable IRRBB in specifications (1) and (2) of both sub-periods, we observe that banks' profitability benefits slightly more from a raise in their interest rate risk exposure over the years 2012-2018.

This might suggest that during the years characterized by extremely low interest rates and a flat yield curve, there might be incentives for banks to take more interest rate risk in their banking book to raise their profitability. Specification (3) reveals a decrease in the contribution to net interest margin from pure loans-deposits intermediation (IRRBB_B) and securities portfolio (IRRBB_S) in the years 2012-2018. Again, a lower and flatter yield curve might clearly be the cause of these results during these years, if compared with the years 2006-2011. On the contrary, the impact of the positions in financial derivatives (IRRBB_D) on NIM seems to be larger than that observed in the years 2006-2011, suggesting that the decrease in banks' NIM associated with the other two components of the overall interest rate risk indicator is balanced out by the positive effect of the derivatives positions.

Overall, the positive and statistically significant regression coefficients of the variable MT1 across all the specifications for both groups of years are consistent with our hypothesis H2 about the benefits of maturity transformation on banks' NIM. It is worth noting that these benefits are more pronounced in the years 2012-2018, relative to the 2006-2011 period. This is in line with the evidence of a positive impact of interest rate risk exposure on net interest margin because the higher is the former, the higher is the maturity transformation activity.

Table 4: The determinants of the net interest margin: whole sample; 2006-2011 (panel A) vs. 2012-2018 (panel B)

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
NIM_{t-1}	0.055***	0.238***	0.216***	0.202***	0.197***	0.201***
	(0.012)	(0.019)	(0.009)	(0.004)	(0.007)	(0.010)
SIZE	-0.040***	-0.022***	-0.019***	-0.050***	-0.033***	-0.032***
	(0.003)	(0.022)	(0.001)	(0.003)	(0.003)	(0.003)
IRRBB	0.078***	0.123***	-	0.105***	0.141***	-
	(0.011)	(0.009)		(0.002)	(0.004)	
IRRBB_B	-	-	0.153***	-	-	0.045***
			(0.005)			(0.017)
IRRBB_S	-	-	0.065***	-	-	0.015***
			(0.009)			(0.004)
IRRBB_D	-	-	0.073***	-	-	0.108***
			(0.011)			(0.035)
MT1	0.063***	0.060***	0.065***	0.304***	0.188***	0.196***
	(0.010)	(0.008)	(0.005)	(0.005)	(0.005)	(0.007)
CR	-0.949***	-0.031	-0.083**	-0.899***	-0.705***	-0.686***
	(0.101)	(0.060)	(0.038)	(0.015)	(0.023)	(0.033)
RA	-0.002***	-0.002***	-0.002***	-0.005***	-0.002***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPGR	-	0.009***	0.009***	-	0.009***	0.008***
		(0.000)	(0.000)		((0.000)	(0.001)
EUR3M	-	0.041***	0.040***	-	-0.007***	-0.007***
		(0.001)	(0.000)		(0.001)	(0.001)
SLOPE	-	0.049***	0.049***	-	0.061***	0.061***
		(0.001)	(0.001)		(0.001)	(0.001)
CONSTANT	1.272***	0.614***	0.600***	1.022***	0.772**	0.736***
	(0.040)	(0.033)	(0.015)	(0.036)	(0.042)	(0.051)
# Obs.	598	598	598	728	726	726
Time fixed effects	YES	NO	NO	YES	NO	NO
Arellano-Bond test for AR(1)	-3.099	-3.971	-2.826	-4.518	-4.633	-4.691
p-value	0.002	0.000	0.005	0.000	0.000	0.000
Arellano-Bond test for AR(2)	-1.369	-1.533	0.142	-0.7519	-1.349	0.404
p-value	0.171	0.125	0.887	0.452	0.177	0.686
Sargan test	20.472	32.876	31.277	72.551	72.387	96.969
p-value	0.367	0.283	0.553	0.622	0.596	0.511

Note: For the definition of the variables, please refer to the previous Table 1. ** and *** indicate statistically significant regression coefficients at the 5% and 1% levels.

4.2.2 The determinants of the interest rate risk exposure

Table 5 reports the results of the analysis of the determinants of interest rate risk exposure, following the model described in equation (2). In specification (1) we use as regressors the bank-specific variables employed in the study of the net interest margin. In specification (2), the two variables related to banks' active and passive operations with the ECB are also considered, and in specification (3) macroeconomic variables are added, replacing the time dummies used to account for fixed temporal effects. Once again, diagnostic tests reported at the bottom of the table regarding serial correlation and the instruments used in the GMM procedure report values that signal the absence of correlation of order 2 and the validity of the instruments.

The regression coefficient of the SIZE variable is negative and statistically significant in all the three specifications for both sub-periods. Therefore, we do not find support to the hypothesis of a higher likelihood of opportunistic behaviour at larger banks. On average, banks with a more intense maturity transformation activity appear more exposed to interest rate risk. Particularly, by separately considering each of the three specifications, we observe that the impact is larger in the years 2012-2018.

Interest rate risk exposure tends to decrease as the share of non-performing loans to total assets (CR) increases in the second of the two sub-periods, indicating a kind of substitution effect between credit risk and interest rate risk: as exposure to the former increases, banks tend to reduce their exposure to the latter. The sign of the regression coefficients is positive in the years 2006-2011. Anyway, the significance of the relationship confirms the importance of considering the impact of interest rate changes on both types of risk.

The level of risk aversion measured by the additional capital endowment over the minimum required (RA) appears positively correlated with interest rate risk exposure in the first of the two sub-periods, although with relatively modest coefficients. Besides being economically irrelevant, the relationship is not statistically significant in the years 2012-2018 for specifications (2) and (3).

The ratio of the ECB funding on total assets (DFB) and that of deposits at the ECB to total assets (LAB) show a change in the sign of their relationship with banks' exposure to interest rate risk over the two sub-periods. An increase in the funds borrowed from the ECB through (targeted) long-term refinancing operations results in greater interest rate risk exposure in the first sub-period, but in a reduction in the years ranging from 2012 to 2018. Deposits at the ECB appear to decrease banks' interest rate risk in the years 2006-2011, while they seem to increase it in the subsequent period.

Overall, it seems that the contribution of long-term refinancing operations, whether targeted or not, in terms of funding stability, translates into a better ability for banks to withstand potential interest rate upward shocks, which is in line with our hypothesis H3. We do not find support to hypothesis H4, according to which, by reducing the average duration of banks' assets, deposits at the ECB should have a positive effect on interest rate risk exposure. This result calls for further investigation.

An increase in slope (SLOPE) leads to a reduction in interest rate risk borne by banks, just as observed with an increase in the GDP growth rate (GDPGR), although the regression coefficients are relatively small in both cases. During the years 2006-2011, the level of interest rates (EUR3M) is positively correlated with interest rate risk, although not significantly, neither from an economic nor statistical point of view. In the years 2012-2018, however, an increase in the 3-month Euribor rate is associated with a reduction in interest rate risk exposure, with a regression coefficient not only significant at the 1% confidence level but also considerably higher, in absolute value, than that of the first sub-period: -0.072 vs. 0.001.

Table 5: The determinants of interest rate risk exposure: whole sample; 2006-2011 (panel A) vs. 2012-2018 (panel B)

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
$IRRBB_{t-1}$	0.149***	0.119***	0.111***	0.035***	0.109***	0.105***
	(0.009)	(0.05)	(0.007)	(0.007)	(0.011)	(0.009)
SIZE	-0.028***	-0.041***	-0.036***	-0.022***	-0.038***	-0.045***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
MT1	0.273***	0.056**	0.146***	0.368***	0.639***	0.592***
	(0.017)	(0.024)	0.012	(0.009)	(0.015)	(0.010)
CR	0.306***	0.158**	0.238***	-0.734***	-0.840***	-0.737***
	(0.112)	(0.049)	(0.046)	(0.028)	(0.029)	(0.025)
RA	0.007***	0.003***	0.005***	-0.003***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DFB	-	0.282***	0.339***	-	-0.454***	-0.461***
		(0.040)	(0.026)		(0.017)	(0.016)
LAB	-	-0.186***	-0.099**	-	0.208***	0.206***
		(0.039)	0.039		(0.027)	(0.027)
GDPGR	-	-	-0.007***	-	-	-0.012***
			(0.000)			(0.000)
EUR3M	-	-	0.001	-	-	-0.072***
			(0.001)			(0.001)
SLOPE	-	-	-0.005***	-	-	-0.030***
			(0.002)			(0.001)
CONSTANT	0.056	0.516***	0.296***	0.134***	0.116**	0.281***
	(0.049)	(0.031)	(0.029)	(0.026)	(0.054)	(0.041)
# Obs.	561	561	561	728	728	728
Time fixed effects	YES	YES	NO	YES	YES	NO
Arellano-Bond test for AR(1)	-3.528	-2.399	-3.178	-5.314	-4.295	-4.514
p-value	0.000	0.016	0.002	0.000	0.000	0.000
Arellano-Bond test for AR(2)	-0.521	-0.606	-0.349	0.802	1.286	1.101
p-value	0.602	0.545	0.727	0.422	0.198	0.271
Sargan test	22.904	11.026	10.922	67.754	99.158	89.376
p-value	0.690	0.855	0.926	0.417	0.196	0.409

Note: For the definition of the variables, please refer to the previous Table 1. ** and *** indicate statistically significant regression coefficients at the 5% and 1% levels.

5. Additional analysis and robustness checks

5.1 Additional analysis

Since we have two types of banks in our sample, we run an additional analysis to investigate whether there are differences in the relations among the variables of interest between the group of cooperative banks and the group of joint-stock intermediaries. To do that, we modify the models in equations (1) and (2) by introducing a dummy variable COOP, which equals 1 in the case of cooperative credit institutions, and 0 for joint-stock banks, and some interaction terms. Particularly, in our analysis of the determinants of our sample banks' NIM, we use COOP × IRRBB to investigate potential differences in the impact of the overall exposure to the interest rate risk in the banking book, COOP × IRRBB_B, COOP × IRRBB_S and COOP × IRRBB_ D, to examine whether there is a difference between cooperative and joint-stock banks in terms of the impact on the net interest margin of the IRRBB exposure stemming from collecting deposits and issuing loans to customers, that associated with the securities portfolio, and the exposure induced by the use of derivatives, respectively. COOP × MIT1 is added in both models presented in equations (1) and (2) to detect potential differences in the impact of the maturity transformation activity on both banks' profitability and interest rate risk exposure, whereas we add in the model of equation (2) studying the determinants of the interest rate risk exposure the interaction terms COOP × DFB and COOP × LAB to examine differences in the relation of the deposits that our banks collect from or have at the European Central Bank and their interest rate risk exposure, respectively. As far as the determinants of net interest margin are concerned, the regression coefficients of the variable COOP × IRRBB in Table 6 show that the positive impact of banks' overall exposure to interest rate risk on their NIM is larger for cooperative banks in the years 2012-2018 for specifications (1) and (2), even if this difference with joint-stock companies is only marginally significant at the 10% confidence level. We do not observe any difference for the impact on NIM of the single components of the overall exposure to interest rate risk: none of the coefficients of the variables COOP × IRRBB_B, COOP × IRRBB_S and COOP × IRRBB_D is statistically significant. Furthermore, there is no statistically significant difference in the impact of the maturity transformation activity on cooperative banks' net interest margin, with the only exception of the regression coefficient of the variable COOP × MT1 in the specification (2) for years 2012-2018, which is however marginally significant at the 10% confidence level. Table 7 reports the results of the analysis of potential differences between the two groups of banks in terms of the determinants of their exposure to the interest rate risk in the banking book. The regression coefficients of the variable COOP × DFB are positive and statistically significant at the 1% confidence level in specifications (2) and (3) for the years ranging from 2006 to 2011. They are not only much smaller but are also marginally significant at the 10% confidence level for the years 2012-2018. Overall, this suggests that the positive impact of the deposits collected from the ECB on IRRBB exposure is stronger for cooperative banks than for joint-stock ones in the first set of years, whereas no difference is found in the relations discussed in the previous section during the years 2012-2018. In the case of cooperative banks, the negative impact of deposits at the ECB is less negative than that observed for joint-stock banks in the years 2006-2011, i.e., the regression coefficients of the interaction term COOP × LAB are positive and statistically significant at the 1% confidence level in specifications (2) and (3) of Panel A, whereas we do not observe any difference for the second sub-period. Overall, we do not observe significant differences between the two groups of banks included in our sample. We argue that, irrespective of their different nature, which allows us to distinguish between cooperative banks and joint-stock companies, it is the type of activity they run as providers of mainly traditional financial products and services to local communities that makes our banks so similar.

Table 6: The determinants of the net interest margin: cooperative banks vs. joint-stock banks; 2006-2011 (panel A) vs. 2012-2018 (panel B)

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
NIM_{t-1}	0.567***	0.465***	0.501***	0.689***	0.555***	0.570***
	(0.027)	(0.030)	(0.031)	(0.015)	(0.016)	(0.025)
SIZE	-0.022***	-0.023***	-0.018***	-0.009***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
COOP	0.000	0.005	0.009	-0.003	-0.003**	0.002
	(0.005)	(0.006)	(0.012)	(0.003)	(0.001)	(0.002)
IRRBB	0.008***	0.003	-	-0.017***	-0.003	-
	(0.003)	(0.004)		(0.004)	(0.003)	
IRRBB_B	-	-	0.010	-	-	0.002
			(0.006)			(0.005)
IRRBB_S	-	-	0.029	-	-	-0.005
			(0.032)			(0.005)
IRRBB_D	-	-	0.010	-	-	-0.006
			(0.013)			(0.005)
MT1	0.002	-0.002	0.000	0.003**	0.005***	0.006*
	(0.002)	(0.003)	(0.005)	(0.001)	(0.002)	(0.003)
COOP × IRRBB	-0.007	-0.003	-	0.015*	0.005*	-
	(0.006)	(0.004)		(0.011)	(0.003)	
COOP × IRRBB_B	-	-	-0.006	-	-	0.000
			(0.006)			(0.005)
COOP × IRRBB_S	-	-	-0.008	-	-	0.007
			(0.033)			(0.005)
COOP × IRRBB_D	-	-	-0.008	-	-	0.009*
			(0.014)			(0.005)
COOP × MIT1	-0.003	-0.004	-0.001	-0.000	-0.004*	-0.005
	(0.007)	(0.003)	(0.006)	(0.001)	(0.003)	(0.003)
CR	0.060***	0.092***	0.050***	0.002	-0.015***	-0.017***
	(0.010)	(0.012)	(0.012)	(0.002)	(0.001)	(0.002)
RA	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPGR	-	0.000	0.000**	-	0.000***	0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
EUR3M	-	0.001***	0.001***	-	0.002***	0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
SLOPE	-	-0.001***	-0.001***	-	0.000***	0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
CONSTANT	0.031***	0.018**	0.010	0.023***	0.016***	0.011***
	(0.006)	(0.008)	(0.014)	(0.004)	(0.003)	(0.003)
# Obs.	578	578	578	721	721	721
Time fixed effects	YES	NO	NO	YES	NO	NO
Arellano-Bond test for AR(1)	-2.991	-3.867	-2.688	-3.999	-4.336	-4.469
p-value	0.001	0.000	0.003	0.000	0.000	0.000
Arellano-Bond test for AR(2)	-1.196	|-1.421	0.124	-0.695	-1.428	0.389
p-value	0.151	0.122	0.776	0.399	0.154	0.556
Sargan test	19.742	29.678	30.165	71.465	70.278	93.434
p-value	0.355	0.277	0.499	0.589	0.531	0.489

Note: COOP is a dummy variable which equals 1 for cooperative banks and 0 for joint-stock banks. COOP × IRRBB, COOP × IRRBB_B, COOP × IRRBB_S, COOP × IRRBB_D are interaction terms of the dummy COOP and IRRBB, IRRBB_B, IRRBB_S and IRRBB_D, respectively. For the definition of the other variables, please refer to the previous Table 1. *, ** and *** indicate statistically significant regression coefficients at the 10%, 5% and 1% levels.

Table 7: The determinants of interest rate risk exposure: cooperative banks vs. joint-stock banks; 2006-2011 (panel A) vs. 2012-2018 (panel B)

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
$IRRBB_{t-1}$	0.092***	0.049**	0.067***	0.149***	0.165***	0.152***
	(0.027)	(0.022)	(0.021)	(0.016)	(0.019)	(0.019)
SIZE	-0.380***	-0.185***	-0.020	-0.021***	0.010	-0.051***
	(0.086)	(0.071)	(0.082)	(0.006)	(0.012)	(0.015)
MT1	0.483***	0.105***	0.146***	0.335***	0.215***	0.639***
	(0.080)	(0.040)	(0.047)	(0.012)	(0.028)	(0.020)
CR	1.233	1.649***	0.985**	-0.035	0.146*	-0.794*
	(0.012)	(0.433)	(0.476)	(0.012)	(0.077)	(0.359)
RA	0.010***	0.008***	0.008***	-0.005***	-0.002***	-0.003***
	(0.000)	(0.003)	(0.002)	(0.000)	(0.000)	(0.001)
DFB	-	1.374***	1.484***	-	-0.122**	-0.0630***
		(0.465)	(0.542)		(0.053)	(0.089)
LAB	-	-0.390**	-0.156**	-	0.225	0.501*
		(0.164)	(0.107)		(0.380)	(0.428)
COOP	0.056	-0.078*	-0.063	0.028	-0.074*	-0.020
	(0.051)	(0.049)	(0.039)	(0.024)	(0.043)	(0.040)
COOP × DFB	-	1.770***	1.558***	-	0.146*	0.186*
		(0.425)	(0.514)		(0.080)	(0.130)
COOP × LAB	-	1.454***	1.121***	-	-0.108	-0.161
		(0.211)	(0.265)		(0.381)	(0.239)
GDPGR	-	-	-0.008***	-	-	-0.018***
			(0.001)			(0.001)
EUR3M	-	-	-0.005***	-	-	-0.056***
			(0.002)			(0.005)
SLOPE	-	-	-0.026***	-	-	-0.029***

			(0.005)			(0.002)
CONSTANT	-0.446***	-0.166	-0.313***	0.029	0.094	0.042
	(0.132)	(0.119)	(0.122)	(0.049)	(0.112)	(0.111)
# Obs.	578	526	526	721	720	720
Time fixed effects	YES	YES	NO	YES	YES	NO
Arellano-Bond test for AR(1)	-3.282	-2.129	-3.178	-4.973	-4.467	-4.617
p-value	0.000	0.013	0.001	0.001	0.001	0.002
Arellano-Bond test for AR(2)	-0.498	-0.592	-0.387	0.802	1.302	1.198
p-value	0.703	0.623	0.683	0.410	0.201	0.312
Sargan test	21.812	10.987	10.391	68.001	98.741	88. 736
p-value	0.590	0.768	0.872	0.524	0.183	0.413

Note: COOP is a dummy variable which equals 1 for cooperative banks and 0 for joint-stock banks. COOP × DFB and COOP × LAB are interaction terms of the dummy COOP and DFB and LAB, respectively. For the definition of the other variables, please refer to the previous Table 1. *, ** and *** indicate statistically significant regression coefficients at the 10%, 5% and 1% levels.

5.2 Robustness checks

Tables 8 and 9 report the results of the robustness tests we have run by replacing the variable MT1, i.e., the inverse of the NSFR, with the ratio of the loans granted to over the deposits collected from customers (MT2). They show that the relations among our variables of interest, as for both the determinants of our banks' profitability and their exposure to interest rate risk in the banking book are confirmed. In comparing Table 8 and Table 9 with Table 4 and Table 5, respectively, we do observe that regression coefficients appear to be smaller when the maturity transformation is measured through our MT2 variable, even if the sign and the overall statistical significance are confirmed.

Table 8: The determinants of the net interest margin: whole sample; 2006-2011 (panel A) vs. 2012-2018 (panel B); new measure of maturity transformation

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
NIM_{t-1}	0.590***	0.471***	0.464***	0.660***	0.487***	-0.494***
	(0.026)	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)
SIZE	-0.026***	-0.023***	-0.020***	-0.008***	-0.005***	-0.005***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IRRBB	0.001**	0.002**	-	0.005***	0.001***	-
	(0.001)	(0.001)		(0.000)	(0.000)	
IRRBB_B	-	-	0.004***	-	-	0.001*
			(0.000)			(0.063)
IRRBB_S	-	-	0.017***	-	-	0.001**
			(0.000)			(0.001)
IRRBB_D	-	-	0.009***	-	-	0.002**
			(0.002)			(0.014)
MT2	0.011***	0.016***	0.012**	0.044***	0.023***	0.073***
	(0.000)	(0.006)	(0.008)	(0.000)	(0.000)	(0.000)
CR	0.055***	0.078***	0.062***	-0.008***	-0.012***	-0.013***
	(0.010)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
RA	0.000***	0.000	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDPGR	-	0.000*	0.000	-	0.000***	0.000***
		(0.088)	(0.090)		(0.000)	(0.001)
EUR3M	-	0.001***	0.001***	-	-0.003***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
SLOPE	-	0.021***	0.031***	-	-0.014***	-0.019***
		(0.000)	(0.000)		(0.000)	(0.000)
CONSTANT	0.027***	0.019***	0.022***	0.020***	0.017***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Obs.	578	578	578	723	723	721
Time fixed effects	YES	NO	NO	YES	NO	NO
Arellano-Bond test for AR(1)	-2.873	-3.652	-2.586	-4.152	-3.965	-4.324
p-value	0.003	0.007	0.006	0.005	0.008	0.009
Arellano-Bond test for AR(2)	-1.289	-1.437	0.124	-0.689	-1.427	0.399
p-value	0.121	0.152	0.753	0.523	0.201	0.621
Sargan test	19.827	31.631	30.829	70.113	70.763	95.696
p-value	0.252	0.321	0.479	0.549	0.632	0.421

Note: For the definition of the variables, please refer to the previous Table 1. ** and *** indicate statistically significant regression coefficients at the 5% and 1% levels.

Table 9: The determinants of interest rate risk exposure: whole sample; 2006-2011 (panel A) vs. 2012-2018 (panel B); new measure of maturity transformation

Variables	Panel A: years 2006-2011			Panel B: years 2012-2018		
	(1)	(2)	(3)	(1)	(2)	(3)
$IRRBB_{t-1}$	0.105*** (0.024)	0.051*** (0.019)	0.049*** (0.017)	0.255*** (0.020)	0.190*** (0.023)	0.143*** (0.014)
SIZE	-0.316*** (0.077)	-0.347*** (0.074)	-0.458*** (0.100)	0.092*** (0.006)	0.055*** (0.014)	0.024** (0.010)
MT2	0.069*** (0.020)	0.074*** (0.014)	0.024*** (0.009)	0.158*** (0.007)	0.161*** (0.012)	0.300*** (0.006)
CR	2.248*** (0.694)	1.217*** (0.443)	1.168*** (0.456)	0.022 (0.043)	0.121* (0.072)	- 0.755*** (0.046)
RA	0.011*** (0.002)	0.009*** (0.002)	0.006** (0.003)	-0.003*** (0.000)	-0.001* (0.001)	- 0.005*** (0.001)
DFB	-	0.025** (0.060)	0.554*** (0.099)	-	-0.129*** (0.026)	-0.028** (0.008)
LAB	-	-1.053*** (0.134)	-0.678*** (0.150)	-	0.088** (0.036)	0.096*** (0.031)
GDPGR	-	-	-0.010*** (0.001)	-	-	-0.002** (0.001)
EUR3M	-	-	-0.001 (0.002)	-	-	- 0.066*** (0.004)
SLOPE	-	-	-0.022*** (0.005)	-	-	- 0.019*** (0.001)
CONSTANT	0.117 (0.152)	0.178** (0.083)	0.353*** (0.116)	0.180*** (0.023)	0.162*** (0.044)	0.261*** (0.029)
# Obs.	578	526	526	723	722	722
Time fixed effects	YES	YES	NO	YES	YES	NO
Arellano-Bond test for AR(1)	-3.221	-1.987	-2.871	-4.789	-3.952	-3.532
p-value	0.004	0.023	0.005	0.003	0.009	0.016
Arellano-Bond test for AR(2)	-0.493	-0.594	-0.481	0.782	1.019	1.093
p-value	0.519	0.455	0.659	0.391	0.183	0.186
Sargan test	22.439	10.763	10.219	63.543	97.128	85.635
p-value	0.592	0.762	0.638	0.289	0.153	0.297

Note: For the definition of the variables, please refer to the previous Table 1. ** and *** indicate statistically significant regression coefficients at the 5% and 1% levels.

6. Conclusions

This study shows that an increased maturity transformation and a higher exposure to interest rate risk in the banking book are positively associated with banks' net interest margin. By analysing the components of interest rate risk exposure, we observe that in the years 2012-2018, the influence of the one stemming from traditional intermediation activity and that associated with the securities portfolio decreases, whereas the one caused by the derivatives positions increases. During the same years, the impact of maturity transformation on the net interest margin shows a significant increase. A more intense maturity transformation activity increases interest rate risk, with a stronger impact during the years 2012-2018. ECB funding determines a raise in interest rate risk exposure in the years 2006-2011, whereas it negatively correlates in the period 2012-2018, thus suggesting that, due to the increased stability of their funding, our sample banks show a better ability to withstand potential increases in interest rates.

Considering the change of the Euro area's monetary policy stance, our findings provide interesting insights into the dynamics involving maturity transformation, profitability, and interest rate risk. The new scenario in which they now run their business calls for a revision of the strategies banks adopted to address the prolonged period of exceptionally low interest rates and requires to carefully assess their ability to cope with the monetary policy normalization process. Identifying and monitoring banks potentially more exposed to interest rate increases is an important priority for policymakers and supervisory authorities; these are two crucial activities to avoid the dangerous negative consequences associated with the conclusion of (T)LTRO programs and the adoption of a restrictive monetary policy such as the one started in the summer of 2022.

Our results should be taken with caution. The sample used in this paper cannot be considered as representative of the entire Italian banking, sector since it is made up of local banks acting on a provincial or regional level. Though many, these banks do not represent the majority of the overall total assets of the Italian banking system. Nevertheless, we do believe it is important to specifically focus also on such a type of banks to tackle the issues we consider in this research, due to the role they have in alleviating small and medium firms' and households' credit constraints. This matters especially in some areas of certain countries which, like Italy, though included into the group of developed countries, are characterized by geographical areas that are not covered by the largest banking groups, neither domestic nor foreign ones. Consequently, our results might give insights that are useful for countries whose banking sectors see the presence of a significant number of small- and medium-sized banks providing traditional financial products and services, like France, Germany and Spain, among the European ones.

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CEO power and bank risk nexus: Evidence from commercial banks in Uganda

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Abstract

This study aimed to establish the nexus between CEO power and bank risk. Previous studies on how CEO power affects risk-taking have produced mixed results. Some studies show that CEO power reduces risk, while others show the reverse. This lack of conclusive findings motivated this study. This study used secondary data from a sample of 14 commercial banks in Uganda covering a period from 2010 to 2020. System GMM was used to establish the relationship between variables, while ARDL was used to infer causality. Findings show that commercial banks with powerful CEOs have lower risk. Such powerful CEOs have prestige power, are internally hired, have ownership, and have served for more than 4 years up to 7 years, and hence possess expert power. We further found a long-run positive relationship between previous bank risk and current bank risk, as well as a causal relationship between CEO power and bank risk. In case there is a need to reduce bank risk in Uganda, making adjustments in CEO power will help. It may also be necessary for persistent adjustment and implementation of decisions and policy actions, if bank risk is to be minimized.

Keywords*:* CEO power, bank risk, Z-score, GMM, agency theory

JEL Classification*:* G30, G32, G39

1. Introduction

A Chief Executive Officer (CEO) can act in the interest of shareholders as per the stewardship theory. However, with excessive power, he/she can make decisions that are not in line with the interests of shareholders (Hua, Song and Talavera, 2019; Berle and Means, 1932) leading to exposing a bank to risk. CEO power includes structural power, ownership power, expert power, prestige power, CEO being a former executive, and CEO being a founder member of the bank. It would be overly high-handed to deny banks the opportunity to undertake risks, or even misleadingly optimistic to expect that the risk level of a bank should be zero. It is through accepting a certain level of risk, that innovation can take place. We acknowledge the scholarly contribution made by the work of Agosto, Cerchiello and Giudici (2023) who emphasized the significance of Environmental, Social and Governance (ESG) factors to the benefit of the best-performing companies in terms of sustainable behaviour and risk management. ESG refers to how businesses promote sustainability, social responsibility and ethical governance practices within their organisation. Similarly, Fafaliou, Giaka, Konstantios and Polemis (2022) argued about the negative impact of ESG factors on reputational risk. As such, we locate the present study in ESG since governance is one of the pillars that contributes to sustainable risk management principles, such as CEO power in the financial sector.

Previous studies on how CEO power affects risk-taking have produced mixed results. Fernandes, Farinha, Martins, Francisco, and Mateus (2021) and Fang, Lee, Chung, Lee and Wang (2020) found that CEO power reduces risk while Hunjra, Hanif, Mehmood and Nguyen (2021) and Altunbaş, Thornton and Uymaz, (2020) found that it increases risk. These mixed findings call for a confirmatory study. Research on CEO power in Africa is also scanty (Anaso, 2020) and no known study has been undertaken regarding CEO power and bank risk nexus in commercial banks in Uganda. Although Uganda has enjoyed relative political and macroeconomic stability over the last thirty years and banks are highly regulated, the banking industry has suffered turbulence with bank closures over that period. In policy, although there is a Financial Institutions Statute (2004), Capital Markets Corporate Governance Guidelines and Table F of Uganda's Companies Act (2012), these do not guide on how CEO power affects risk-taking of banks.

2. Review of theoretical and empirical literature

Various theories have been advanced to explain the dimensions of CEO power and the effect of CEO power on bank performance outputs. The two key theories underpinning CEO power are the upper echelons theory (Hambrick and Mason, 1984) and the agency theory (Berle and Means, 1932; Jensen and Meckling, 1976; Fama and Jensen, 1983). Background theories include stewardship theory (Donaldson and Davis, 1991), resource-based theory (Wernerfelt, 1984 and later developed by Penrose, 1959) and the social network theory (Saidu, 2019; Kavitha and Bhuvaneswari, 2016) which guide CEO power. Risk frameworks and theories include portfolio theory/model, contracting model, regulatory hypothesis theory, risk balancing hypothesis and the Managerial overconfidence hypothesis. These theories underpin the various risks faced by a bank including liquidity risk, market risk, credit risk, operational/transactional risk, external business risk, legal and regulatory risk, liquidity risk, foreign exchange risk, interest rate risk, counterparty risk, reputation risk, fraud risk, strategic risk, technology risk, off-balance sheet risk, governance risk and solvency risk (Gurendrawati *et al.*, 2021; Osayi, Dibal and Ezuem, 2019; Okafor and Fadul, 2019; Buston, 2015; Ishtiaq, 2015; Shafique, Hussain and Hassan, 2013; Abu and Al-Ajmi, 2012; Hassan, 2011; Kuritzkes and Schuermann, 2010; Al-Tamimi and Al-Mazrooei, 2007; Crouhy, Galai and Mark, 2006; Bessis, 2002; Pyle, 1999; Santomero, 1997). Ferretti and Gonnella (2021), after studying an Italian bank, found that bank CEOs have hubris which can be seen in the CEO's relations with the self, with others and with the world. This prevents them from following good advice, leads to poor governance, and consequently to financial distress. A powerful CEO with hubris will lead to a bank facing excessive risk.

CEOs intervene in company affairs, and this affects risk taking behaviour. We thus seek to assess how these various CEO powers affect bank risk. Structural power comes from a CEO holding a high position in the organisation's hierarchy, having many positions and many titles and where one holds both the title of CEO and that of Board Chairman culminating into CEO/Chair duality (Hemdan, Suhaily and Ur Rehman, 2021; Saidu, 2019). A CEO who chairs the board and also operates the firm influences decisions of the board and can easily implement his/her decisions. That CEO also has a role in channelling a bank's strategy since the board influences the strategy of a bank as was found by Ferretti, Gonnella and Martino (2024) in their assessment of Italian banks. After a study of Chinese banks for the period 2006 to 2016, Fang *et al.*, (2020) found that bank risk taking is significantly improved by CEO structural power. Wang (2018) while studying listed banks in Mainland China, Hong Kong and Taiwan found that separating the CEO role from the chairman of the board increased the risk-taking behaviour of banks.

Regarding ownership power, an individual holding shares in a company gives that individual advantage over others. The higher the percentage of shares one holds, the more power has such an individual (Hamidlal and Harymawan, 2021). Where a CEO is also a shareholder, his/her interests will be in sync with those of the other shareholders hence reducing the information and decision asymmetry that exist between shareholders and managers arising out of the agency problem. Monitoring costs will be reduced with higher managerial/ director ownership because when the ownership of a CEO in the firm increases, it will result in the convergence of interests between company CEO and shareholders (Florackis, 2008; Jensen and Meckling, 1976).

Expert power is where a CEO exhibits extraordinary experience and knowledge of the tasks done, and decisions made and is thus considered to be an expert. A CEO who has worked in different industries, companies and organizations has a lot of experience which can benefit the bank (Li and Patel, 2019). The professionalism and expertise of the CEO tend to improve with longer tenure (Hamidlal and Harymawan, 2021). Individuals who have served longer than others are believed to have experience, and are believed to serve better. Although a long CEO tenure increases CEO entrenchment, Mostafa, Hasnan and Saif (2021) believe that an entrenched CEO is more involved in activities that increase corporate values.

Prestige power arises out of personal status, respect, admiration accorded to the person, reputation and connections that one has and other people's perception of that person's influence through contacts and qualifications. The reputation one has acquired in the office, positive perceptions that he/she has, relationships with external parties like government coupled with a good educational background reflect that person's power (Saidu, 2019; Fetscherin, 2015). Prestige power gives the CEO confidence to take on more successful projects as he/she will be comparing himself to other successful CEOs or getting advice. Such CEOs are likely to make decisions that align with the company's best interests (Fang *et al.*, 2020; Saidu, 2019). This will reduce the risk of failure. However, very powerful CEOs tend to take on more risk by over-investing (Barnea and Rubin, 2010).

A CEO being a former executive is another source of power. The resource-based view encourages firms to depend on their internal resources to improve performance. One of the executives can be promoted to the position of CEO. Such a move will be less costly in terms of hiring and orienting the individual (Saidu, 2019; Wernerfelt, 1984). An internally appointed CEO will have more power than one who is hired from outside of the organization, since the former will have more information about the firm. This move is motivating to the individual and will enable him/her to work towards the expansion and sustainability of the firm. However, such a CEO may suffer from 'arrivalism', that is, the excitement of attaining a leadership position, as he/she may want to show other employees that he/she is now more powerful than them. Such excitement may lead to reckless behaviour, thereby exposing the bank to more risk. Barron, Chulkov and Waddell (2011) opined that hiring a CEO from within the firm prevents discontinuation of operations due to the similarity-attraction as would be for a CEO hired from outside and this reduces risk. A CEO hired from outside the bank would lead to some temporary discontinuation of operations as they need time to study the firm. Such CEOs come with a mandate for strategic change which may or may not be successful.

CEO being a founder member is another source of power. Where a founder member becomes CEO, he/she attains power (Hemdan, Suhaily and Ur Rehman, 2021). The performance of founder and non-founder CEOs differs significantly with regard to achieving organizational goals (Abebe and Alvarado, 2013) since founder CEOs have more commitment to the firms they founded. They look at the firm as part of them, and its growth is their growth; as opposed to non-founder CEOs who look at the firm as one of those which they will serve and move on. A founder will be eager to see the bank survive, and will therefore take less risk. However, to expand widely, such a CEO may take on too much risk and this overconfidence may lead to more risks (Yi, Jiatao and Yu, 2015).

The review above shows mixed findings regarding the effect of CEO power on bank risk. The dimensions of CEO power largely have a contradicting relationship to bank risk in different studies. When it comes to Uganda, no related literature in this field of study is available.

3. Research Methodology

3.1 Data and sample

The banking market in Uganda comprises of 25 commercial banks, of which four are domestic and the others have foreign ownership. This study used secondary data to establish the nexus between CEO power and bank risk in commercial banks in Uganda covering a period from 2010 to 2020. A list of commercial banks as of the data collection date is as captured below:

Table 1: List of commercial banks operating in Uganda

Bank name	**Market capitalisation (US$)**	**Assets under management (Uganda Shillings)**
ABC Bank Uganda Limited	Not listed	62.1 billion
Absa Bank Uganda Limited	Not listed	4210.0 billion

Bank of Africa Uganda Limited	Not listed	1100.1 billion
Bank of Baroda Uganda Limited	US$81.08m	2138.9 billion
Bank of India Uganda Limited	Not listed	333.3 billion
Cairo Bank Uganda Limited	Not listed	193.4 billion
Centenary Rural Development Bank Limited	Not listed	4499.9 billion
Citibank Uganda Limited	Not listed	1200.8 billion
Development Finance Company of Uganda Limited (DFCU)	US$45.50m	3539.4 billion
Diamond Trust Bank Limited	Not listed	1774.7 billion
Ecobank Uganda Limited	Not listed	997.0 billion
Equity Bank Uganda Limited	US$1209.35m	3459.6 billion
Exim Bank (Uganda) Limited	Not listed	407.0 billion
Finance Trust Bank Limited	Not listed	393.9 billion
Guaranty Trust Bank (Uganda) Limited	Not listed	251.1 billion
Housing Finance Bank Limited	Not listed	1914.2 billion
I&M Bank Uganda	Not listed	866.4 billion
KCB Group Uganda Limited	US$736.81m	657.3 billion
NCBA Bank Uganda	Not listed	823.0 billion
Opportunity Bank Uganda Limited	Not listed	262.0 billion
Stanbic Bank Uganda Limited	US$512.55m	8572.2 billion
Standard Chartered Uganda Limited	Not listed	3617.2 billion
Tropical Bank Limited	Not listed	310.5 billion
United Bank for Africa Uganda Limited	Not listed	492.5 billion
Postbank Uganda Limited	Not listed	815.4 billion

Source: Bank of Uganda (2024); individual bank websites.

Of the banks in Table 1 above, the listed banks include Bank of Baroda, DFCU Bank, Stanbic Bank Uganda, Equity Bank Limited and KCB Group. The majority of the commercial banks in Uganda are not listed on a stock exchange, but are all under the centralised supervision of the Bank of Uganda. Although Uganda has a total of 25 commercial banks, the final sample was purposively selected and comprised of 14 banks which had full information for the period under review, resulting in a balanced panel giving 140 data points. While carrying out panel research in banks, banks that do not have full information can be left out of the sample, as was done by La Torre, Bittucci, Paccione and Palma (2024) in their study aimed at evaluating the sustainability profile of banks through a comprehensive benchmarking analysis in the Italian context. The same approach was also applied by Menicucci and Paolucci (2020) while gathering evidence from Italian financial institutions on whether gender diversity matters for risk-taking. Data were obtained from sources included the individual bank annual reports, electronic and print media, websites, and the World Bank database and reports, all of which are in the public domain.

3.2 Measurement of variables

The independent variable was CEO power ($CEOP_{it}$) including structural power, ownership power, expert power, prestige power, CEO being a former executive of that bank and founder CEO. Structural power ($STRP_{it}$) was measured based CEO duality, ownership power ($OWNP_{it}$) was measured using the percentage of shareholding of the CEO, expert power ($EXPP_{it}$) was measured using CEO tenure, prestige power ($PREP_{it}$) was binary where a code of “1” was given if CEO also holds other directorships and “0” otherwise, CEO being a former executive, that is, Internally-hired ($CFEP_{it}$) was coded “1” if CEO was an executive before appointment as CEO, and “0” otherwise and founder CEO ($CFOP_{it}$) was binary coded “1” if CEO is also a founder member, and “0” otherwise.

The dependent variable, bank risk, (BR_{it}) was measured using the Z-score which shows bank stability (Hua *et al.*, 2019;). Control variables are included to normalise the results for better and more reliable inference. Bank size ($BKSZ_{it}$) was measured as the logarithm of total banks assets, listing status ($LSST_{it}$) was coded 1 for a listed bank, otherwise zero, Gross Domestic Product (GDP) growth ($GDPG_t$) was measured by GDP growth for year *t* rate is measured relative to last year's GDP, and non-performing loans was measured by the absolute figure of non-performing loans.

3.3 Model specification

In line with Altunbaş *et al.* (2020) and Wooldridge (2010), a simple unobserved panel data model for the study is specified as below:

$$BR_{it} = \alpha_0 + \alpha_1 CEOP_{it} + \delta X_{it-1} + D_t + \varepsilon_i \quad (1)$$

Where:

BR_{it} is risk taking of the bank i in period t as measured by the Z-score. $CEOP_{it}$ represents an index of CEO power. X_{it-1} is a vector of other bank-specific characteristics commonly employed in the bank risk literature that include measures of bank size, listing status, Gross Domestic Product (GDP) growth, nonperforming loans and unemployment. D_t is a dummy variable meant to capture any structural breaks in the model. ε_{it} is the error term.

The two-step System Generalised Method of Moments (GMM) model by Arellano and Bond (1991), Holtz-Eakin *et al.*, (1990) and Arellano and Bover (1995) was applied to examine the relationship between CEO power and bank risk since this study has lagged endogenous variables as instruments and cross-section fixed effects. The GMM model in banking research was also applied by Barra and Ruggiero (2023) in their assessment of the effect of bank-specific factors on credit risk in Italian banks. The GMM-based estimator allows for efficient estimation in the presence of arbitrary heteroscedasticity, helps to overcome the challenge of endogeneity, solves the problems of serial correlation and takes advantage of the use of orthogonal conditions (Leitao, 2010; Hansen, 2000). GMM handles modelling concerns such as fixed effects and endogeneity of regressors, while at the same time avoiding dynamic panel bias, accommodating unbalanced panels and multiple endogenous variables (Roodman, 2009; Nickell, 1981).

To test the causality relationship between CEO power and bank risk, we used the Auto Regressive Distributed Lag (ARDL) where causality was inferred from the significance of the Error Correction Term (ECT) (for joint causality), long-run coefficients (for long-run causality) and short-run coefficients (for short-term causality) (Gwachha, 2023; Narayan, 2004). A negative ECT implies the presence of causality.

The basic ARDL model is specified as:

$$BR_{it} = \alpha_0 + \sum_{k=1}^{\rho} \emptyset_k BR_{it-k} + \sum_{k=0}^{q} \varphi_k' X_{it-k} + \varepsilon_{it} \quad (2)$$

Where $\emptyset_k$ and φ_k are the coefficients of the lags of the dependent variable and the independent variables respectively. The lags in equation (2) imply a set of dynamic responses in bank risks (BR) to any given change in explanatory variables (x). There is an immediate response followed by short run and long run responses. Reparameterization of the model in equation (2) gives rise to the error correction version of the ARDL model shown in equation 3:

$$\Delta BR_{it} = \beta_0 - \alpha[BR_{it-1} - \theta' X_{it-1}] + \sum_{k=1}^{\rho-1} \gamma_k \Delta BR_{it-1} + \sum_{k=0}^{q-1} \lambda_k' \Delta X_{it-k} + \varepsilon_{it} \quad (3)$$

In the model specified in equation (3), X and BR are as defined earlier on, $\alpha = 1 - \sum_{k=1}^{\rho} \emptyset_k$ is the speed of adjustment coefficient and $\theta = \frac{\sum_{k=0}^{q} \varphi_k}{\alpha}$ is a vector of long run coefficients. γ and λ are the short run coefficients and the term in the brackets is the Error Correction Term.

4. Data analysis and discussion

4.1 Descriptive Statistics

Table presents the summarised statistics for the variables resulting from the pooled estimations:

Table 2: Summary statistics for variables used in the pooled estimation (2010 - 2020)

Variables	Obs	Mean	Std, Dev,	Minimum	Maximum
CORE	154	15.34	11.97	0.06	39.68
OWNP	154	0.00000227	0.0000104	0.00	0.00005
EXPP	154	3.59	2.78	0.70	14.00
PREP	154	0.23	0.42	0.00	1.00
CFEP	154	0.28	0.45	0.00	1.00
STRP	154	0.00	0.00	0.00	0.00

CFOP	154	0.00	0.00	0.00	0.00
CEOP	154	0.4	0.49	0.00	1.00
CEOP_INDEX	154	- 0.00	1.14	-3.76	2.42
BKSZ	154	27.18	1.23	23.06	29.32
LSST	154	0.45	0.50	0.00	1.00
GDPG	154	5.09	1.78	3.00	9.40
NPL	154	27,400,000,000	36,700,000,000	0	219,000,000,000
UNEMPL	154	2.44	0.72	1.91	3.59

Note: These are raw data derivations before transformation.

Source: Authors' own computation

Note: Z-score is proxy for bank risk. CEOP is CEO power. STRP is structural power. OWNP is Ownership power. EXPP is Expert power. PREP is Prestige power. CFEP is CEO being a former executive, i.e., Internally-hired. CFOP is CEO founder. BKSZ is Bank size. LSST is Listing status. GDPG is Gross Domestic Product (GDP) growth. NPL is Non-performing loans. UNEMPL is Unemployment.

Table shows the summary of descriptive statistics for the pooled results for all the banks in this study covering the period 2010 – 2020. The descriptive statistics reflect that bank risk, as measured by the Z-score, was at an average of 15.34. A bank with a high Z-score is unlikely to default and is therefore seen as having low risk (Tran *et al.*, 2019). Using this figure alone is not sufficient to conclude whether banks in Uganda have a high risk or low risk since the Z-score can be interpreted relatively and not absolutely. However, the table also shows that banks in Uganda had a Z-score with a minimum of 0.06 and a maximum of 39.68 over the research period implying that the level of risk in commercial banks in Uganda varies tremendously among banks and is not the same with a range of 39.62 and a standard deviation of 11.97. Ownership power (OWNP) by CEOs reflected minimal influence on bank risk. Our results show that there are banks where the CEO has no shareholding, and so yield little power.

On the other hand, expert power (EXPP), indicated by CEO tenure, is low and does not change by a large margin as shown by the standard deviation of only 2.79 years. On average, most CEOs have spent 3.59 years as CEOs. Those CEOs with more years of experience increase value as was alluded to by Chiu, Chen, Cheng and Hung (2019) and Wu, Quan, and Xu (2011) who found that a CEO with experience can deal with environmental dependency, has cognitive work experience gained with time and can deal with critical contingencies is said to have expert power.

This further confirms the findings of Byrd, Cooperman and Wolfe, 2010) who concluded that the tenure of bank CEOs was between 3 and 6 years. In Uganda, CEOs do not derive a lot of power from other directorships, as reflected by prestige power (PREP). However, the few that have other directorships have more power than those who do not, as was also suggested by Yusuf, Abubakar, Aliyu and Aneitie (2022). Ugandan commercial banks reflected a 28% internal hire where the CEO was a former executive (CFEP). This is contrary to the findings of Agrawal, Knoeber and Tsoulouhas (2006) who concluded that firms will always opt for insiders to take on CEO position, as this is at a low rate among commercial banks in Uganda.

4.2 Correlation results

Bivariate correlation was done to measure the strength and direction of the linear association between two variables. The Pearson correlation coefficient results are shown in Table 3 below:

Table 3: Correlation matrix

Variables	Z-SCORE	CEOP	CFEP	EXPP	GDPG	LSST	NPL	OWNP	PREP	UNEMPL	BKSZ
Z-SCORE	1.000										
CEOP	0.034*	1.000									
CFEP	0.052*	0.117*	1.000								
EXPP	0.139**	0.472***	0.052*	1.000							
GDPG	-0.008*	-0.090*	0.013*	-0.084*	1.000						
LSST	0.096**	-0.062*	0.050*	0.045*	0.038**	1.000					
NPL	0.021*	0.058*	0.209***	0.255***	-0.161***	0.093*	1.000				
OWNP	0.360***	-0.177***	-0.136**	-0.137**	-0.036**	0.242***	-0.021*	1.000			
PREP	0.339***	0.337*	0.067*	0.063*	-0.027**	-0.097*	0.037*	-0.121*	1.000		
UNEMPL	-0.043*	-0.233***	-0.038*	-0.159**	0.272***	0.179**	-0.227***	-0.121*	-0.084*	1.000	
BKSZ	0.102*	0.194**	0.187**	0.441***	-0.118*	0.399***	0.505***	0.158**	0.139**	-0.238***	1.000

Source: Authors' own computations

Note: Z-SCORE is proxy for bank risk. CEOP is CEO power. OWNP is Ownership power. EXPP is Expert power. PREP is Prestige power. CFEP is CEO being a former executive i.e. Internally-hired. BKSZ is Bank size. LSST is Listing status. GDPG is Gross Domestic Product (GDP) growth. NPL is Non-performing loans. UNEMPL is Unemployment

* significant at 10%; ** significant at 5%; *** significant at 1%.

There was a positive relationship between ownership power and Z-score (r = 0.36) indicating that the more a CEO owns shares in the bank, the less risky the decisions they will make, and hence the bank will experience less risk. The possible explanation for this is that share ownership by the CEO creates a sense of cautiousness, care and concern for the survival of the bank. Pathan (2009) found that CEO ownership is negatively related to systematic risk. There is a positive relationship between expert power and Z-score (r = 0.139) indicating that the more experienced the CEO, the lower the bank risk. The findings are in line with those of Hemdan, Suhaily and Ur Rehman (2021) who found that an experienced CEO can deal with environmental dependency, has learned the dynamics of running a bank in Uganda, has cognitive work experience gained with time, and can deal with critical contingencies, hence exposing the bank to less risk. However, these findings contradict the managerial entrenchment theory which considers long-serving managers as becoming entrenched and therefore following personal interests and not organizational interests.

With regards to prestige power, there was a positive relationship between prestige power and Z-score (r = 0.339); confirming that the more prestigious a bank CEO in Uganda is either through his connections, education or directorships in other firms, the lower the bank risk of the bank in which he or she is CEO. In addition, where the CEO was a former executive of the bank, we found this to be positively correlated with the Z-score (r = 0.052), indicating that commercial banks in Uganda whose CEOs were former employees before being appointed into CEO positions, have lower bank risk. These findings justify the resource-based theory's assertion that the valuable resources that a firm has access to like employees and managers, if deployed well as vital intellectual capital can improve that firm's competitive advantage (Daryaee, Pakdel, Easapour and Khalaflu, 2011; Barney, 2001; Wernerfelt, 1984; Penrose, 1959). A person promoted to the CEO position from within the bank has an interest in the bank's growth and knowledge of the bank's internal and external operating environments will reduce the bank's risk exposure.

CEO power had a positive relationship with Z-score (r = 0.034). This implies that the more power a CEO has, the lower the bank risk. The possible explanation is that when a CEO is powerful, they will have confidence in making quick decisions and will be able to deploy resources, both human and financial, to ensure that the bank runs successfully and remains solvent, hence reducing risk.

Regarding the control variables, there was a positive relationship between bank size and the Z-score (r = 0.102). This affirmed that as commercial banks expand in Uganda, they lower bank risk probably due to the large assets base and liquidity. This confirms the finding of Cipollini, Ielasi and Querci (2024) who aver that systematic risk is significantly driven by bank size. Listing status had a positive relationship with the Z-score (r = 0.096). This suggests that when a bank gets listed, bank risk reduces probably because getting listed increases public confidence and scrutiny. However, high market power may reduce public scrutiny of the bank (Cardillo, Cotugno, Perdichizzi and Torluccio, 2024) hence exposing it to more risk. There was a negative relationship between GDP growth and the Z-score (r = - 0.008), implying that a low rate of GDP growth will increase the Z-score and accordingly decrease bank risk probably because during recess and slowdown in economic activity in Uganda, banks will be reluctant to give out loans because the ability for borrowers to pay back is perceived to be low. This perceived increase in credit risk exposure will lead to banks' lending less hence a decrease in bank risk.. There was a positive relationship between non-performing loans and the Z-score (r = 0.021), suggesting that when nonperforming loans increase, bank risk decreases probably because when more people start to pay back their loans, the bank's exposure to credit risk, the threat of insolvency and default risk reduces. Exposure to credit risk could also probably reduce due to automation of the credit risk assessment as was the case in Italy (Branzoli, Rainone and Supino, 2024). Commercial banks in Uganda also impose restrictions over the use of encumbered assets and this could have reduced exposure to risk since bank systematic risk is affected by changes in the encumbered assets (Cipollini, Ielasi and Querci, 2024). Table 3 also shows a negative relationship between unemployment and the Z-score (r = -0.043). As such, when unemployment increases, the Z-score reduces, thus bank risk increases probably because when more people who have bank loans stop working, they will not be able to pay back the loans. As more and more people lose jobs or fail to get jobs, banks perceive a higher loan default rate and an increase in credit risk.

4.3 GMM results for the relationship between CEO power and bank risk

Table below presents the results of the relationship between CEO power and bank risk for 2010-2020 using the system GMM technique. The GMM estimator is consistent since the null hypothesis for the Hansen test is not rejected and the presence of first-order serial correlation (AR1) and the absence of second-order serial correlation (AR2) are confirmed. The Hansen test checks the validity of instruments (Dahir, Mahat and Ali, 2018).

Table 4: Control variables as determinants of bank risk

	2-Step System GMM Model
Variables	Z-score
L.Z-score	0.354^{***}
	(0.0956)
CEOP	-3.168^{*}
	(1.369)
NPL	2.210^{*}

	(0.934)
GDPG	0.199***
	(0.0360)
UNEMPL	0.791**
	(0.263)
BKSZ	2.012**
	(0.671)
LSST	-2.946*
	(1.447)
N	126
Groups	14
Instruments	12
AR(1)	-3.05*
AR(2)	-0.84
Sargan test	3.60
Hansen test	3.98

Source: Authors' own computations.

Note: Z-score is proxy for bank risk. CEOP is CEO power. BKSZ is Bank size. LSST is Listing status. GDPG is Gross Domestic Product (GDP) growth. NPL is Non-performing loans. UNEMPL is Unemployment. AR(1) is autoregression of order 1. AR(2) is autoregression of order 2.

* significant at 10%; ** significant at 5%; *** significant at 1%.

The coefficient of the relationship between the previous year's bank risk (L.Z-score) and the current year's bank risk (Z-score) is positive and significant. The relationship between current and previous bank risk is positive and significant, confirming a long-run positive relationship between previous bank risk and current bank risk. A unit change in the previous year's bank risk level will lead to an increase in the current year's bank risk by 0.354. This shows that bank risk is persistent over time and cannot just be eliminated instantly. It has a persistent behaviour in that the bank risk faced by a given bank in a certain year depends on the bank risk of the respective bank for the previous year. If, in a given year, banks take steps to reduce risk, it will take a year to realize the effect of those efforts. This is consistent with theoretical models which allude that bank risk is persistent (See Dahir *et al.*, 2018; Bharati and Jia, 2018) and should be managed gradually.

CEO power (CEOP) has a negative and statistically significant impact on Z-score. A unit change in CEO power leads to a 3.168 units' reduction in Z-score hence an increase in bank risk. This implies that as CEO power increases, bank risk increases in the long-run. The plausible reason might be that whenever a CEO is entrusted with a lot of power, he or she will be ambitious, have hubris, have overconfidence and will take many decisions without consulting. These findings are consistent with the findings of Barnea and Rubin (2010) and Malmendier and Tate (2015) who found that very powerful and entrenched CEOs tend to take on more risk by over-investing.

Control variables including non-performing loans, economic growth, unemployment and bank size had a positive impact on the reported Z-score, while listing status exerted a negative effect on the Z-score. A unit increase (decrease) in these measures will lead to an increase (decrease) in the Z-score, hence a decrease (increase) in bank risk.

In the absence of independent directors on the board, a positive and statistically significant impact of non-performing loans (NPL) on the Z-score is reported, translating to a decrease in bank risk, as more people start to pay back their loans, the bank's exposure to credit risk and default risk reduces and so does the threat of insolvency. Similarly, economic (GDP) growth has a positive relationship with Z-score. A unit change in GDP growth will lead to an increase in the Z-score by 0.199 without board independence, implying that as economic growth increases, the Z-score will also increase, thus leading to a decrease in bank risk and this positively enhances bank stability. When economic growth is positive, commercial banks in Uganda lend out more money on the assumption that borrowers are capable of paying back the loans since the economy is growing and there is more economic activity and more money generation. These findings are consistent with those of Khan, Scheule and Wu (2017) who found that GDP growth leads to revenue growth; so, borrowers will be expected to repay loans, hence reducing the bank credit risk. Also, GDP growth implicitly assures that bank lending will function effectively and there will be a reduction in the incidence of non-performing loans.

A unit change in unemployment leads to a significant increase of 0.791 units of the Z-score without board independence. When there is a decline in unemployment, borrowing rates tend to be low as banks tighten their lending policies, hence reducing default risk and hence risk of insolvency. We further found that bank size has a positive relationship with the Z-score. A unit change in the size of a commercial bank will lead to an increase in the Z-score, hence a change in bank risk by 2.012 when the board is not independent, alluding to that as bank size increases, bank risk will decrease. When banks expand, their resilience increases and their large assets base and liquidity increase, which makes it possible for them to reduce unnecessary investment and lending out money. Since these banks are already established, their ambition for expansion and lending is low, hence their low risk-taking behaviour. These results align with those of Adusei (2015) who found that bank size reduces bank risk.

Lastly, listing status has a negative relationship with the Z-score without board independence. When listing status increases by one unit, the Z-score reduces by 2.946 units hence increasing bank risk. This confirms that when a bank is listed, the risk to which it is exposed increases due to the additional pressure to generate earnings originating from the public. This pressure can inadvertently force the banks to take on several projects on an urgent need to expand, which increases their risk. Further to this, by listing the bank, there will be more outside shareholders whose individual monitoring of the bank will be limited. These findings are in line with those of Alsharif (2020) who found that the pressure to generate earning, which is exerted on listed companies by the public intending to invest or the shareholders, also encourages banks to increase risk. Moreover, agency problems derived from the separation of ownership and control make publicly listed banks riskier than their unlisted peers.

4.4 Causality results

Using ARDL, causality was inferred from the significance of Error Correction Term (ECT) (for joint causality), long-run coefficients (for long-run causality) and short-run coefficients (for short-term causality) (Gwachha, 2023; Narayan, 2004). A negative ECT implies the presence of causality. The causality effect of CEO power on bank risk was established using the ARDL PMG results as shown in Table 5 below:

Table 5: ARDL results for PMG

	PMG
	D.Z-score
Long-run	
L.CEOP	8.461^{***}
	(17.62)
ECT	-0.0258^{***}
	(3.37)
Short-run	
D.CEOP	0.151
	(0.28)
_cons	-1.015
	(-1.24)
N	140

Source: Authors' own compilation

Note: Z-score is proxy for bank risk. CEOP is CEO power. ECT is Error Correction Term.

** significant at 10%; ** significant at 5%; *** significant at 1%.*

From Table 5 above, ECT is negative (- 0.0258) which shows that there is a causal relationship between the CEO power and bank risk. CEO power has a long-run positive and significant causal impact on the Z-score and reduces bank risk with a coefficient of 8.461, significant at the 1% level. This implies that changes in CEO power will cause a change in bank risk in the long run. There is however no short-run causality. Any changes in CEO power will have an impact on bank risk only in the long run. Where there are changes in CEO power to reduce bank risk, the results will be seen in the long run. This is because of the need for the CEO to first adjust to the new position especially if he/she has just been appointed. For a CEO of a commercial bank to be able to reduce bank risk in Uganda, they must first study the environment, get acquainted with it, and introduce strategies gradually but consistently. This will lead to a reduction of bank risk in the long run. These findings are consistent with those of Victoravich, Buslepp, Xu and Grove (2011) who concluded that the short-term decisions of a CEO can impact the bank in the long run. As chief planners, CEOs are considered architects of the long-term strategy of the firm (Sheikh, 2019). Since ECT is negative and significant, it can be concluded that there is joint causality of the independent variables of CEO power on bank risk. A significant coefficient of 8.461 shows that there is a positive causality between CEO power and the Z-score, implying that CEO power causes the Z-score to increase showing a reduction in bank risk.

4.5 Robustness Checks

Using the Jarque-Bera test, data was found to be normally distributed. Using the Arellano-Bond test for autocorrelation, there was no problem of autocorrelation or serial correlation. VIF was used to measure multicollinearity and all values were less than 5, which implies that there was no problem of multicollinearity in all the models. Pesaran's test was used to establish any cross-sectional independence among the variables, and none was established. Using the Breusch-Pagan test for heteroskedasticity, we discovered that the data had a problem of heteroscedasticity with $X^2 = 6.71$ and a p-value of 0.0096, which led to the rejection of the null hypothesis of constant variance or absence of heteroscedasticity. To curb this problem, and to correct for heteroskedasticity, we ran our models using robust standard errors that are not affected by outliers and other data irregularities. Robust standard errors can be used to run regression models in cases where heteroskedasticity exists (Huang, Wiedermann and Zhang, 2022). All models were run with the number of instruments (13) less than the number of groups (14), confirming that the models were robust. The Sargan test and Hansen test were used to establish the validity of the instruments and the robustness of the model, respectively. The instruments were found to have validity.

5. Conclusion, recommendations and limitations

This study concludes that, among commercial banks in Uganda, banks with lower bank risk are headed by CEOs with more power. The more shares a bank CEO in Uganda owns in the respective bank, the less risky the decisions they will make and, hence the bank will experience less risk. Furthermore, the more prestigious a CEO is either through his networks, connections, education or other directorships, the lower the bank risk. Similarly, where a CEO was a former employee before being appointed to that position, there will be low bank risk probably due to vested interests and familiarity with the bank operations. Also, the actions of powerful CEOs cause a reduction in bank risk in Uganda especially in the long run. There is a joint causality of the elements of CEO power on bank risk in the long run. Despite using Uganda as the unit of analysis, these findings can be generalised to commercial banks in other developing countries, as most of these financial institutions adhere to Basel III, which globally regulates banks insofar as risks are concerned, and equally exposed to the actions of their respective CEOs.

The most relevant CEO power elements in Uganda affecting bank risk include expert power, prestige power, ownership power and the CEO being a former executive or internally hired. Although it is not common to have owners as CEOs of commercial banks in Uganda, for the years when the situation was such in certain commercial banks, such banks exhibited less risk. CEO tenure should be maintained between 4 and 7 years for effective management of risk, since the higher the CEO tenure, the lower the bank risk. From a policy and regulation perspective, it is recommended that the Central Bank of Uganda and the Uganda Stock Exchange continue to closely monitor the actions of CEOs regarding their role in influencing bank risk. Specific statements in this regard should be put in the Financial Institutions Statute and the Uganda Securities Guidelines for Banks.

This study had some limitations, which can be overcome by future research. The sample was based on Uganda as the unit of analysis. In order for findings on CEO power and bank risk to be impactful, comparative analysis can be undertaken across regions, and economic blocs. Similarly, the period of study can be extended beyond the ten years used herein, so that the effect of structural breaks can be considered. Agosto *et al*.'s (2023) study particularly underpins the role of statistical learning and artificial intelligence methods in the financial sector. As governance is one of the factors encompassed in ESG, future studies on governance in the financial sector of developing countries could combine different ESG scores into a single ESG index thereby enabling comparative analysis across firms within the sector.

Author contributions

These authors contributed equally.

Conflicts of interest

The authors declare no conflict of interest.

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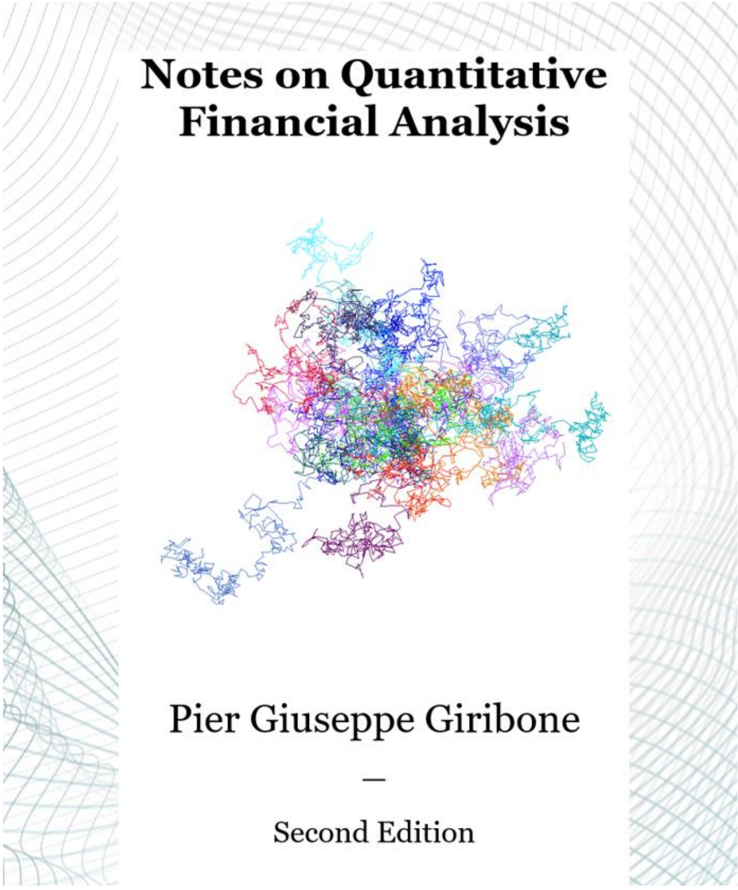

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Below is a brief summary of the covered topics:

Part I: Fixed Income Instruments

The first chapter is a summary of the main concepts of financial mathematics underlying quantitative analysis, up to the modeling of the interest rates term structure.

The second chapter shows the different types of bonds present in the financial markets, together with the assessment of the risks that an analyst must manage.

The third part explores the heart of quantitative analysis, introducing the best practices for estimating the fair value of a bond, together with its risk measures (duration, modified duration and convexity).

Part II: Futures and Forwards

After the description of the basic concepts for understanding this category of derivatives, the second chapter introduces the specific quantitative analysis of these instruments, with a particular focus on pricing and hedging.

Part III: Options

Given the inherent variety of topics connected to options, this section has been thoroughly covered. In addition to the description of the standard pay-off, the first chapter deals with the foundations of this derivative and introduces the mathematical properties, including the put-call parity.

The second chapter concerns the pricing of plain-vanilla options. The well-known Black-Scholes-Merton pricing framework has been introduced, showing how it can be applied to options written on different underlyings (equity, index, rates, futures and currencies). In addition to the fair value, the sensitivities (Greeks) are also estimated.

The third chapter deals with option strategies: combinations of plain-vanilla options with underlying and with other options, in order to create specific hedging and trading strategies. Among the strategies, covered call, protective put, bull/bear spread, butterfly spread, straddle, strip, strap and strangle are covered.

The fourth chapter reviews the main non-standard (i.e. exotic) options, characterized by special pay-offs. The lognormal pricing framework is extended to these types of options; among them: forward start, cliquet, digital, chooser, compound and path-dependent (barrier, Asian and lookback) options.

Not all options can be adequately priced using a closed formula. For those characterized by particularly non-linear pay-offs or by early exercise features, a numerical methodology has to be implemented.

Chapter 5 is therefore dedicated to binomial stochastic trees, particularly useful for dealing with derivatives characterized by the possibility of being exercised in advance, while chapter 6 is dedicated to the Monte Carlo technique, which is considered suitable for representing any type of pay-off, thanks to its flexibility. The working principle, the internal consistency, the pricing estimation, and the computation of the most important risk measures are illustrated for both algorithms. Once the reader has become confident on the correct approach for the quantitative analysis of the derivative, it is time to focus on the inputs of the model.

Finally, Chapter 7 centers on determining the inputs for the previously exposed techniques. A particular focus has been given to the estimation of volatility (both historical and implied) and to the correlation.

Part IV: Swaps

Similarly to the previous scheme, the section dedicated to swaps is divided into two parts: the first chapter describes the fundamentals of the different types of swaps, while the second deals with the quantitative analysis of the instrument. Particular attention is paid to Interest Rate Swaps (IRS) and Currency Swaps. Two distinct valuation approaches are provided, i.e. considering the derivative as a portfolio of forward contracts, or as two positions (one long and one short) in two bonds. The second chapter concludes with the derivation of long-term spot rates from Interest Rate Swaps, a process known as swap curve stripping.

Part V: Credit Derivatives

This section consists of only one chapter in which Credit Default Swaps (CDS) are presented. It describes how premiums can be used to compute risk-adjusted discount factors in a fixed income instrument pricing context. The chapter ends with an introduction of the most popular models among analysts for the pricing of these derivatives.

Part VI: Inflation

This section covers the main inflation-linked derivatives: Zero-Coupon Inflation-Indexed Swap (ZCIIS) and Year-on-Year Inflation-Indexed Swap (YYIIS). The standard market approach is presented to simulate the prospective values of the CPI preparatory to the pricing of these instruments with particular focus on the modeling of seasonality. The chapter concludes with the case study of "BTP Italia", an exotic security linked to Italian inflation characterized by a non-standard pay-off.

Part VII: Aggregate Risk Measures

The risk measures discussed so far have addressed the single instrument and can hardly be extended to a portfolio, characterized by instruments of a different financial nature. Considering this need, the most common approaches to estimating Value-at-Risk have been introduced: parametric, full-evaluation, Monte Carlo backward and forward looking. The Expected Shortfall and the importance of conducting stress tests and back tests are briefly presented as well.

Part VIII: Credit Risk

The first chapter analyzes the determinants of the Demand and Supply of credit and provides a summary for the core elements that constitute a mortgage/loan: interest rate, repayment plans, mode of extinction, amount and Loan-to-Value, guarantees, duration and the Global effective annual rate.

The second chapter focuses on the definition and on the mathematical models for estimating counterparty risk, which can be interpreted by its nature as a hybrid between financial risk and credit risk.

In particular, it has been shown that the probability of default can be inferred from Credit Default Swap (CDS) premiums, listed bond spreads or stock prices using the KMV (Kealhofer, Merton and Vasicek) model.

The last part of the chapter highlights the structural limits of counterparty risk, validating the need to provide a more complete definition of credit risk. Credit risk is based on three pillars: the probability of default (PD), the Loss Given Default (LGD) and the Exposure at Default (EAD). An effectual discussion is dedicated to each of these three important components.

The third chapter presents the statistical approaches that allow the estimation of PD starting from historical data (not necessarily market data), among which, the Altman's Z-Score, the Logit-Probit and the CreditGrades models are covered.

The fourth chapter introduces the regression models suitable for estimating and forecasting the Loss Given Default.

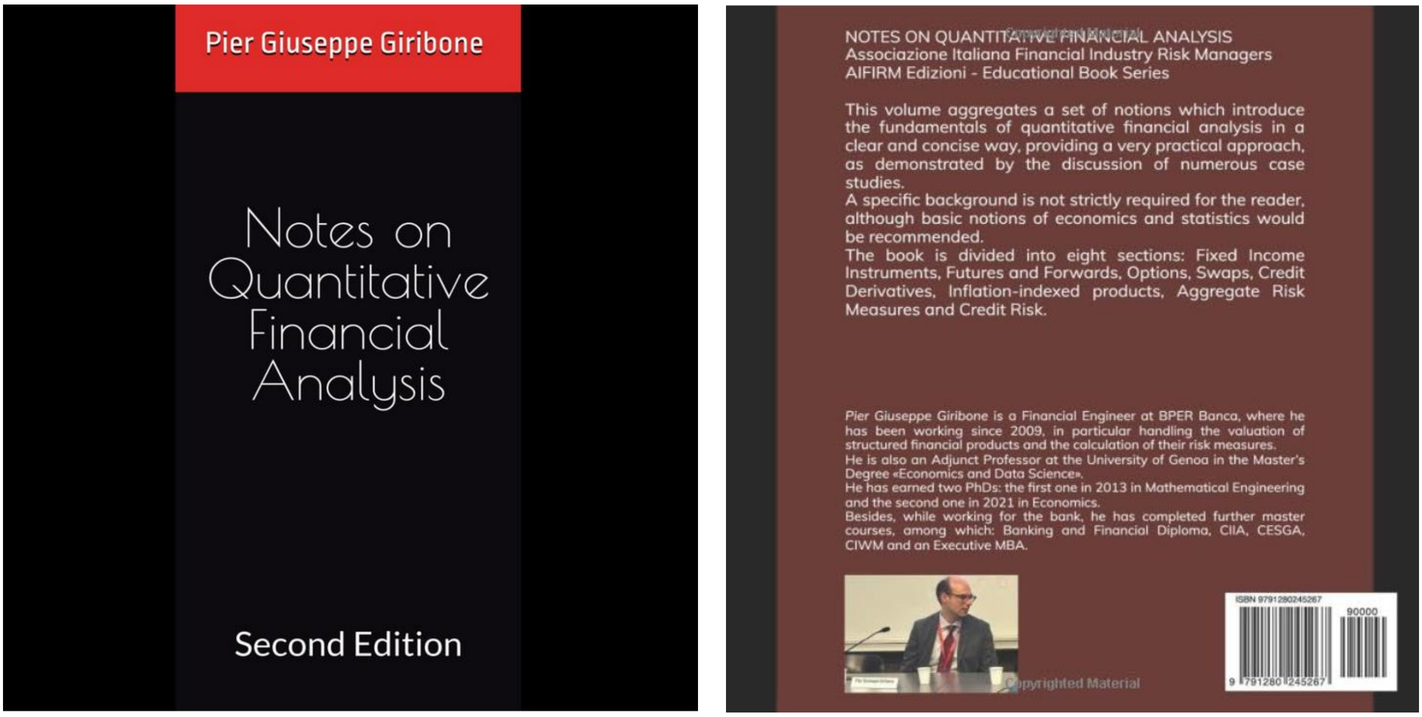
The fifth chapter deals with the estimation and the predictive models for EAD. In this context, a Monte Carlo model is introduced for the determination of the Credit Valuation Adjustment (CVA) with particular attention to the modeling of the Expected Exposure to the various future time buckets. Once the reader has acquired the required knowledge for a correct credit measurement, we move on to the concept of rating systems.

The sixth chapter introduces Rating Agencies and provides the basic notions for creating transition matrices. The Cohort approach and the Hazard approach are adequately discussed with the relative methods of calculating confidence intervals.

The seventh chapter deals with credit risk managed not on a single position, but at portfolio level. In this phase asset correlation has to be presented and, to this end, the Moment matching and the Maximum Likelihood approaches are explained. An example of estimating a Monte Carlo VaR and a C-VaR is also provided in the credit context.

The part dealing with credit concludes with the main methods for validating credit models. Among those, the Cumulative Accuracy Profile (CAP), the Receiver Operating Characteristics (ROC), the binomial test and the Brier Score are covered.

At the end of each chapter, further food for thought is provided through a bibliography of reference papers or books, which allow useful insights into each topic covered.



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About the artist

Daniele Prencipe is a Savonese intellectual whose knowledge spans from philosophical to mathematical subjects, from technical/computer science to artistic ones.

A common factor with the author of the book is the passion for abstract disciplines and for grasping how they can, covertly yet so profoundly, influence our daily reality with elegance and lightness.

The ink drawings placed at the end of the sections of this book are part of the works included in the "Man and Structure" collection of drawings.

The first exhibition where Daniele exhibited these works was in Milan in Villa Litta in the summer of 1977. For further information, please refer to the single volume of this artistic exhibition.

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