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The interplay between accounting quality and credit default risk for banks

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Abstract

I explored the relationship between accounting quality and credit default risk for banks in the Eurozone. I set a model of banks in Orbis from 2015 to 2023. I aimed to broaden the literature on the banking sector since it has been largely neglected because of its particular balance sheet and financial measures. In agreement with previous findings, the Wilcoxon test revealed that the IFRS 9 mandatory adoption decreases the credit default risk for banks in the Eurozone. The results are accurate after robustness checks. However, this study is limited to the Eurozone. Further, since IFRS was often adopted along with concurrent institutional reforms, it is difficult to identify the real effects of IFRS. To my knowledge, it is the first study that analyzes the relationship between accounting quality and credit default risk for banks from an accounting perspective in the Eurozone since previous scholars focused on capital-market impacts. This study contributes to developing a promising line of research in accounting and finance. Further, another implication would be to incentivize policymakers to focus on the improvement of institutional settings rather than the harmonization of accounting standards.

Keywords Accounting Quality, Bank, IFRS, Risk

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1. Introduction

Institutional differences across countries result in information asymmetry in financial reports (Brown, 2016). For this reason, International Reporting Standards (IFRS) generate comparability, permitting to investors process more information (Gao et al., 2019). Accordingly, there has been increasing interest in understanding the economic consequences derived from this set of accounting standards (Leuz & Wysocki, 2016). To date, IFRS 9 facilitates the provision of future credit losses (Novotny-Farkas, 2016; Kyiu & Tawiah, 2023), playing a crucial role for banks by mitigating their upward and downward movements derived from economic cycles (Bushman & Williams, 2012).

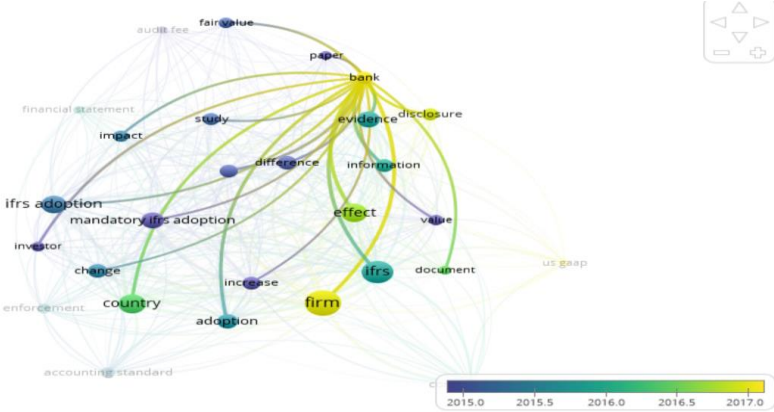
Hence, I aimed to broaden the literature on the banking sector as it has been largely neglected by previous scholars because of its particular balance sheet and financial measures (Beatty & Lino, 2014) and, concerning the IFRS, previous scholars mainly concentrated on investigating its role in enhancing comparability (Barth et al., 2012; Landsman et al., 2012; Lin et al., 2019; Conaway, 2022). Regarding the effect of IFRS on banks, previous scholars (Kim et al., 2011; Ball & Shivakumar, 2015; Brown, 2016) mainly focused on understanding its role in terms of contractability. Further, as IFRS 9 mandatory adoption has been in effect since January 1, 2018 (HSBC Holdings plc, 2018), studies are scarce on this topic, being a promising line of research.

This study aligns with Kyiu and Tawiah (2023) by attempting to understand the impact of IFRS 9 on banks risk. However, since their study considered stocks return as a *proxy* for banks risk, addressing a call by Leuz and Wysocki (2016), I went beyond the capital-market effect and considered the real impacts of IFRS on credit default risk for banks from an accounting perspective. According to Bitar et al. (2018), credit default risk is one of the primary risks a bank can face, constituting along with operational and market risk, the first pillar of the Basel II Accord.

For this reason, I proposed the following research question: *Does accounting quality impact credit default risk for banks in the Eurozone?* In agreement with Lamoreaux et al. (2015), I defined accounting quality as the mandatory adoption of IFRS. The election for banks is due to their relevant role in an economy (Berger et al., 2020). The selection for the Eurozone is justified by the fact that the effects of IFRS are more pronounced in countries with strong regulatory systems (Barth et al., 2012). Concerning the objective, I analyzed the relationship between accounting quality and credit default risk for banks. This study, to my best knowledge,

However, although the banking sector has been largely neglected by previous scholars (Beatty & Lino, 2014), the term *bank* indicates it is gaining more attention on IFRS-related topics from scholars in the last years (see Figure 2).

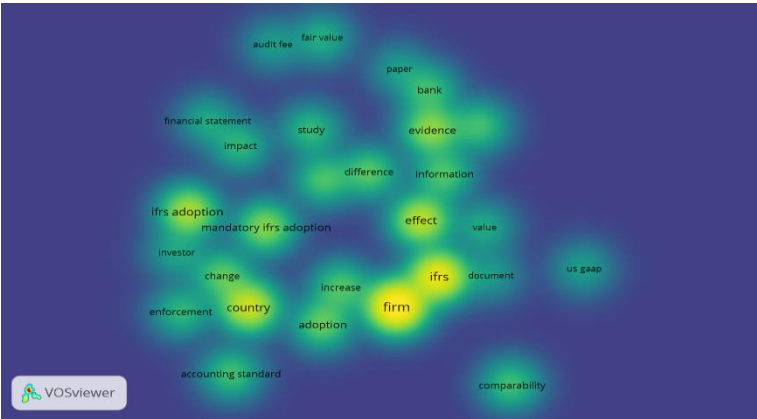
Figure 2. Evolving of the banking sector in studies on IFRS



Source: Self-elaborated from VOSviewer (2024).

However, by applying *Density Visualization*, which provides an overview of the most researched topics in a bibliometric analysis (VOSviewer, n.d.), it presents a pronounced focus on IFRS in firms (see Figure 3).

Figure 3. Most research topics on IFRS



Source: Self-elaborated from VOSviewer (2024).

The importance of executing an analysis of bibliometric networks on previous studies on IFRS was to reinforce the selection for examining the impact of IFRS 9 on banks, which is an underexplored topic, but which is gaining ground in recent years.

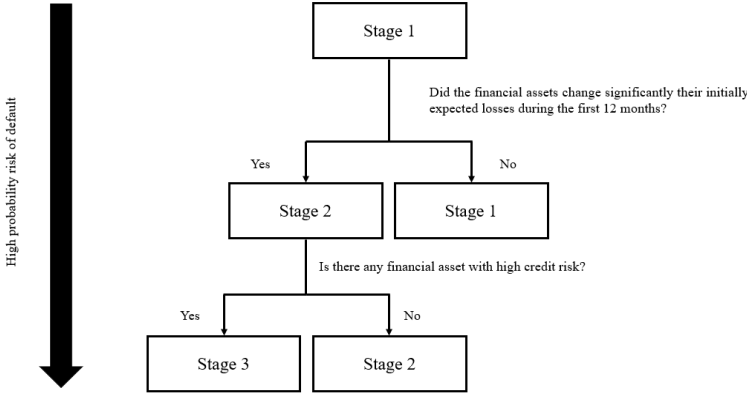
3. IFRS 9 conceptualization and its importance

IFRS 9 plays a crucial role for banks by mitigating their pro-cyclicality (Bushman & Williams, 2012). IFRS 9 has been in force since January 1, 2018 (HSBC Holdings plc, 2018). IFRS 9 aims to address the complexity of its predecessor, IAS 39 (PwC, n.d.). While IAS 39 advocated for calculating the provisions through incurred losses only when the evidence of a loss was pronounced, IFRS 9 estimates both the current and expected losses (Kyu & Tawiah, 2023; Bank for International Settlements, n.d.).

IFRS 9 defines how financial firms should measure both assets and liabilities. The main objective of this financial statement is an annual assessment of their assets and their depreciation (Bank for International Settlements, n.d.). Although this financial statement increases provisions in financial reports under IFRS 9 (Kyu & Tawiah, 2023), as banks must report previous events, current financial situation, and forecast of credit risk management (Bank for International Settlements, n.d.), the likelihood of a bank taking on risky investments is smaller because of credit loss provisions (Novotny-Farkas, 2016).

IFRS 9 presents three stages better illustrated in Figure 4.

Figure 4. Framework on the three stages of IFRS 9



Source: Self-elaborated from Kyu and Tawiah (2023).

4. Literature review

4.1 Accounting quality

Historically, each nation has structured its own accounting standards. However, the global integration in the capital market has been requiring a harmonization of financial reports (Judge et al., 2010). Accordingly, IFRS is a worldwide attempt to achieve comparability (Conaway,

2022). The importance of enhancing comparability is the promotion of a sound capital market, permitting an increase in the foreign investments flow (DeFond et al., 2011). Over the years, various countries adopted IFRS to mitigate information asymmetry (Leuz & Wysocki, 2016).

From a banking perspective, the main focus of this study, Kim et al. (2011) analyzed the effect of the voluntary adoption of IFRS by borrowers on the loan contracts of a cross-country sample of non-US firms throughout 18 years. They found that banks define lower rates to IFRS adopters and set out less strict covenants. Ball and Shivakumar (2015) examined several features of IFRS that may affect the debt contracts of banks. They highlighted significant declines of covenants used by banks after the adoption. DeFond et al. (2015) observed that IFRS adoption does not impact the crash risk of financial firms. Nevertheless, by considering financial firms based in countries with poor banking regulations, IFRS leverages these risk ratios. Brown (2016) explored the changes in using private debt covenants post-IFRS adoption. The findings are aligned with previous results studies by evidencing the reduction in the bureaucracy of contracts after IFRS adoption. López-Espinosa (2021) investigated a cross-country sample of banks and they pointed out that expected credit losses (ECL), which is advocated by IFRS, are more accurate than incurred credit losses (ICL), a normative from IAS 39, in forecasting banks risk. Nonetheless, by using a cross-country sample of banks, Kyiu and Tawiah (2023), one of the first scholars who investigated the impact of IFRS 9 on banks risk, revealed a bank risk decrease after IFRS 9 adoption. Conversely, Leuz and Wysocki (2016) debated the economic consequences derived from regulations in financial reports, including the IFRS, in a cross-country approach, and they did not evidence of the real effects of regulations in financial statements.

In this section, I included studies related to the capital-market standpoint, as previous scholars have largely considered this sector to assess the real effect of IFRS on the financial results of adopters and the perception of stakeholders in the financial market. Loureiro and Taboada (2015) uncovered a strong relationship between IFRS adoption and mergers and acquisitions (M&A) deals and stock returns. Gao et al. (2019) verified whether firms can improve their liquidity and value after IFRS adoption. They found that IFRS adoption benefits them. Liu et al. (2023) analyzed how the mandatory adoption of IFRS by publicly listed firms in the European Union (EU) affects its peer private firms. They highlighted that IFRS decreases significantly the capital investment of private firms.

Finally, the selection of articles on comparability, the most researched topic by previous scholars, is justified since harmonization in financial reports drives a decrease in the expected risk (Kim et al., 2016). Barth et al. (2012) examined whether IFRS adoption by non-US firms enhances comparability and, as a result, they pointed out a greater increase. Landsman et al. (2012) explored whether information on earnings management in financial reports increased after IFRS adoption. They revealed an increase in this attribute in 16 countries. Lin et al. (2019) investigated the effectiveness of mitigating information asymmetry by comparing global and local standards in the German context. The results evidenced an increase in comparability after the IFRS mandatory adoption in 2005. However, this adoption does not lead to an incremental increase in comparability after this period. Conversely, Conaway (2022) verified the temporal trend in comparability for a cross-country sample. They uncovered that firms that adopted local standards are more comparable than IFRS adopters.

To better illustrate the reviewed literature on IFRS effect on banks and firms, Table 2 summarizes the main findings discussed in this section.

Table 2. The main findings on IFRS effect on banks and firms

| <i>Perspectives</i> | <i>Authors</i> | <i>Dependent variables</i> | <i>Relationship between IFRS adoption and the dependent variables</i> |
|---------------------|------------------------------|--|---|
| Banking | Kim et al. (2011) | Rates and strictness of loan contracts | - |
| | Ball and Shivakumar (2015) | Debt contracts of banks | - |
| | De Fond et al. (2015) | Likelihood of crash risk | No evidence |
| | Brown (2016) | Reduction of contractability | + |
| | López-Espinosa et al. (2021) | Prediction of banks risk | + |
| | Kyiu and Tawiah (2023) | Banks risk | - |
| Capital-market | Loureiro and Taboada (2015) | M&A and stocks returns | + |
| | Leuz and Wysocki (2016) | Economic consequences | No evidence |
| | Gao et al. (2019) | Firm value and liquidity | + |
| | Liu et al. (2023) | Capital investments | - |
| Comparability | Barth et al. (2012) | Comparability | + |
| | Landsman et al. (2012) | Comparability | + |
| | Kim et al. (2016) | Perception of risk | - |
| | Lin et al. (2019) | Comparability | + |
| | Conaway (2022) | Comparability | Local standards > IFRS |

Source: Self-elaborated (2024).

By analyzing Table 2, it is possible to infer a strong theoretical framework for the positive impact derived from IFRS adoption.

For this reason, I proposed the following hypothesis.

H1: Accounting quality decreases the credit default risk for banks.

5. Methodology

5.1 Sample

The data were gathered from the Orbis database, which is a platform that contains business and financial information of private and public firms in Europe (European University Institute, n.d.), for 9 years (2015–2023). I included 68 active banks whose size classification is defined as *very large* and *large* because they have greater financial and tangible resources (Knight and Kim, 2009). However, since the dependent variable is credit default risk for banks (*BankRisk*) and considering other explanatory and control variables of Equation (1), 36 banks were dropped from the sample. Further, 2 banks were removed due to missing values. Accordingly, the definitive sample consists of 30 bank-year observations (see the list of banks in Table 3). The unique macroeconomic variable (*GDP*) was obtained from the International Monetary Fund (IMF) (International Monetary Fund, 2024).

5.2 Measuring the credit default risk for banks

In agreement with Bitar et al. (2018), the dependent variable on credit default risk for banks is measured in three ways. The primary measure (*BankRisk*) is the loan loss reserves to total assets ratio. It identifies the loan quality of a bank and, the higher the value, the more the precautionary reserve policy is. To ensure robustness, I also used two *proxies* for credit default risk for banks. My first alternative measure (*BankRisk01*) used loan loss reserves to gross loans. My second alternative measure (*BankRisk02*) utilized loan loss reserves to impaired loans. To better illustrate it, Table 4 outlines all variables that integrate my sample.

5.3 Measuring the explanatory variables

Concerning the IFRS, in conformity with Liu et al. (2023), there are three explanatory variables. I used a dummy variable (*PreIFRS*) that coded 1 for the three years before the adoption of IFRS 9 (2015–2017) and 0 otherwise. Next, a dummy variable (*IFRSRollout*) that coded 1 for the three years during the rollout period (2018–2020) and 0 otherwise. Finally, a dummy variable (*PostIFRS*) that coded 1 for the three years after the rollout period (until 2023)

and 0 otherwise. In agreement with Isidro et al. (2015), the selection for a period of three years is justified by its suitability to detect longer-term effects derived from IFRS 9 adoption.

5.4 Control variables

In line with previous studies (Laeven & Levine, 2007; Bhagat et al., 2015; Bitar et al., 2018; Elnahass et al., 2021; Kyiu & Tawiah, 2023), the model included several bank characteristics which are expected to influence the credit default risk for banks.

Efficiency (*Efficiency*). This variable is measured as the cost-to-income ratio. It reflects the bank overheads, mainly represented by salaries. Accordingly, the higher the value, the less efficient the bank is (Bitar et al., 2018).

Gross domestic product (GDP) growth (*GDP*). This variable captures the growth of an economy (Kyiu & Tawiah, 2023).

Income diversity (*IncomeDiversity*). This variable captures the degree to which banks diversify between lending and non-lending activities. Hence, the higher the value, the greater the diversification (Laeven & Levine, 2007). It is calculated as follows.

$$IncomeDiversity = 1 - \left| \frac{(Net\ interest\ income - Other\ operating\ income)}{Operating\ income} \right|$$

Natural logarithm of total assets (*LnSize*). This variable influences bank performance since larger banks present greater financial assets and market share (Beck & Demirguc-Kunt, 2006).

Natural logarithm of tangible equity (*LnTangible*). This variable removes intangible assets from the calculation of an equity base of a bank (Bitar et al., 2018). It is measured as the natural logarithm of the ratio of tangible equity of a bank to total assets.

Ratio of net loans to total loans (*NetLoans*). A bank that possesses a diversified loan portfolio is less exposed to risk. Therefore, the higher the value, the lesser the exposition to risk (Bitar et al., 2018).

Return on average assets (*ROAA*). This variable captures bank profitability (Kim et al., 2011).

According to Bhagat et al. (2015), investment banks take on more risk than commercial banks. Accordingly, I used a dummy variable to control bank classification ($\sum Classification$), coding 1 for investment banks and 0 otherwise.

Further, during the COVID-19 outbreak, banks experienced poor financial performance (Elnahass et al., 2021). Hence, I used a dummy variable to control the COVID effect ($\sum COVID$), coding 1 for the COVID-19 period (2020) and 0 otherwise.

In order to address my hypothesis, I proposed Equation (1), (2), and (3).

Equation (1).

$$\begin{aligned} BankRisk = & \beta_0 + \beta_1*PreIFRS + \beta_2*IFRSRollout + \beta_3*PostIFRS + \beta_4*Efficiency + \beta_5*GDP \\ & + \beta_6*IncomeDiversity + \beta_7*LnSize + \beta_8*LnTangible + \beta_9*NetLoans + \\ & \beta_{10}*ROAA + \sum Classification + \sum COVID + \varepsilon \end{aligned}$$

Equation (2).

$$\begin{aligned} BankRisk01 = & \beta_0 + \beta_1*PreIFRS + \beta_2*IFRSRollout + \beta_3*PostIFRS + \beta_4*Efficiency + \\ & \beta_5*GDP + \beta_6*IncomeDiversity + \beta_7*LnSize + \beta_8*LnTangible + \\ & \beta_9*NetLoans + \beta_{10}*ROAA + \sum Classification + \sum COVID + \varepsilon \end{aligned}$$

Equation (3).

$$\begin{aligned} BankRisk02 = & \beta_0 + \beta_1*PreIFRS + \beta_2*IFRSRollout + \beta_3*PostIFRS + \beta_4*Efficiency + \\ & \beta_5*GDP + \beta_6*IncomeDiversity + \beta_7*LnSize + \beta_8*LnTangible + \\ & \beta_9*NetLoans + \beta_{10}*ROAA + \sum Classification + \sum COVID + \varepsilon \end{aligned}$$

6. Data analysis

6.1 Descriptive statistics

Figure 5 displays descriptive statistics across 270 bank-year observations from 2015 to 2023. The results were obtained from jamovi, a statistical software (jamovi, n.d.). To begin with, the primary measure of credit default risk for banks (*BankRisk*) evidences a mean of 0.0273, ranging from 0 to 0.231. Concerning the alternative measures, the primary one (*BankRisk01*) exhibits a mean of 4.2834, with values from 0.152 to 31.955. Regarding the second one (*BankRisk02*), it presents a mean of 62.0957, ranging from 11.353 to 405.043.

Concerning the explanatory variables, *Efficiency* displays a mean of 62.29, with values from 20.876 to 108.968. *GDP* introduces a mean of 1.7156, with values from -11.200 to 13.800. *IncomeDiversity* evidences a low value of merely 0.2302, ranging from -0.947 to 5.259, indicating poor diversification. *LnSize* exhibits a mean natural logarithm of 18.2075, with values from 12.028 to 21.607. In parallel with their sizes, *LnTangible* presents a mean natural

logarithm of 15.4812, ranging from 10.811 to 18.169. *NetLoans* displays a low value of 0.6158, with values from 0.207 to 2.708, indicating a high exposure to risk because of their low diversification loan portfolio. Finally, *ROAA* evidences a mean of 0.5660, ranging from -46.369 to 15.310.

Figure 5. Descriptive statistics

| | N | Missing | Mean | Median | SD | Minimum | Maximum |
|-----------------|-----|---------|---------|---------|---------|---------|---------|
| BankRisk | 270 | 0 | 0.0273 | 0.0146 | 0.0402 | 9.06e-4 | 0.231 |
| BankRisk01 | 270 | 0 | 4.2834 | 2.4546 | 5.4935 | 0.152 | 31.955 |
| BankRisk02 | 270 | 0 | 65.9536 | 62.0957 | 38.7808 | 11.353 | 405.043 |
| Efficiency | 270 | 0 | 62.2904 | 60.4182 | 13.0753 | 20.876 | 108.968 |
| GDP | 270 | 0 | 1.7156 | 2.0000 | 3.9248 | -11.200 | 13.800 |
| IncomeDiversity | 270 | 0 | 0.2302 | 0.2059 | 0.6636 | -0.947 | 5.259 |
| LnSize | 270 | 0 | 18.2075 | 18.3268 | 2.2196 | 13.028 | 21.607 |
| LnTangible | 270 | 0 | 15.4812 | 15.8620 | 2.0164 | 10.811 | 18.169 |
| NetLoans | 270 | 0 | 0.6158 | 0.5886 | 0.3570 | 0.207 | 2.708 |
| ROAA | 270 | 0 | 0.5660 | 0.6304 | 3.5318 | -46.369 | 15.310 |

Source: jamovi (2024).

6.2 Correlation

To begin with, Figure 6 shows the correlation values of the variables in Equation (1) obtained from jamovi. Overall, the correlation matrix displays weak correlations, suggesting that no variables directly influence the measures of credit default risk for banks (*BankRisk*, *BankRisk01*, and *BankRisk02*). Intuitively, the only strong correlation is between *LnSize* and *Tangible* (0.981***).

Figure 6. Correlation matrix

| | BankRisk | BankRisk01 | BankRisk02 | Efficiency | GDP | IncomeDiversity | LnSize | LnTangible | NetLoans | ROAA |
|-----------------|----------|------------|------------|------------|--------|-----------------|----------|------------|----------|------|
| BankRisk | — | | | | | | | | | |
| BankRisk01 | 0.976*** | — | | | | | | | | |
| BankRisk02 | -0.061 | -0.046 | — | | | | | | | |
| Efficiency | 0.033 | 0.049 | 0.030 | — | | | | | | |
| GDP | 0.006 | 0.027 | 0.029 | -0.061 | — | | | | | |
| IncomeDiversity | 0.109 | 0.173** | -0.182** | -0.144* | 0.097 | — | | | | |
| LnSize | -0.170** | -0.179** | -0.180** | 0.106 | -0.088 | -0.024 | — | | | |
| LnTangible | -0.121* | -0.137* | -0.163** | 0.081 | -0.094 | -0.028 | 0.981*** | — | | |
| NetLoans | 0.009 | -0.043 | -0.044 | -0.106 | -0.024 | -0.022 | 0.017 | 0.135* | — | |
| ROAA | -0.192** | -0.192** | 0.046 | -0.089 | -0.007 | -0.034 | -0.098 | -0.094 | 0.025 | — |

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

Source: jamovi (2024).

6.3 Ordinary least squares

In Gretl, a software-oriented for econometric analyses (Gretl, n.d.), I considered the primary measure of credit default risk for banks (*BankRisk*) with the explanatory and control variables of Equation (1). By executing the ordinary least squares (OLS) and selecting the option for considering robustness, three variables were removed from the model due to collinearity (i.e., *IFRSRollout*, *PostIFRS*, and \sum *COVID*). The obtained results are expressed in Table 5.

Table 5. OLS for *BankRisk*

| | <i>Coefficient</i> | <i>Standard Error</i> | <i>t-value</i> | <i>p-value</i> | |
|-----------------|--------------------|-----------------------|----------------|----------------|-----|
| const | 0,0756641 | 0,0296853 | 2,549 | 0,0117 | ** |
| PreIFRS | 0,0303275 | 0,00558923 | 5,426 | <0,0001 | *** |
| Efficiency | 0,000314652 | 0,000301477 | 1,044 | 0,2981 | |
| GDP | 7,14070e-05 | 0,00116428 | 0,06133 | 0,9512 | |
| IncomeDiversity | 0,00484685 | 0,00455095 | 1,065 | 0,2884 | |
| LnSize | -0,0359972 | 0,0101182 | -3,558 | 0,0005 | *** |
| LnTangible | 0,0381770 | 0,0111650 | 3,419 | 0,0008 | *** |
| NetLoans | -0,0259874 | 0,00933480 | -2,784 | 0,0060 | *** |
| ROAA | -0,00186019 | 0,00137551 | -1,352 | 0,1781 | |
| Classification | -0,0238807 | 0,00981563 | -2,433 | 0,0160 | ** |

** *p*-value < 0.05, *** *p*-value < 0.01

Source: Self-elaborated from Gretl (2024).

Next, I considered the first alternative measure of credit default risk (*BankRisk01*) with the explanatory and control variables of Equation (2). By executing the ordinary least squares (OLS) and selecting the option for considering robustness, one variable was removed from the model due to collinearity (i.e., *PostIFRS*). The obtained results are expressed in Table 6.

Table 6. OLS for *BankRisk01*

| | <i>Coefficient</i> | <i>Standard Error</i> | <i>t-test</i> | <i>p-value</i> | |
|-----------------|--------------------|-----------------------|---------------|----------------|-----|
| const | 10,8677 | 2,78061 | 3,908 | 0,0005 | *** |
| PreIFRS | 4,43401 | 0,665037 | 6,667 | <0,0001 | *** |
| IFRSRollout | 1,99002 | 0,516758 | 3,851 | 0,0006 | *** |
| Efficiency | 0,0533236 | 0,0318374 | 1,675 | 0,1047 | |
| GDP | 0,0256757 | 0,0979678 | 0,2621 | 0,7951 | |
| IncomeDiversity | 1,68562 | 0,759751 | 2,219 | 0,0345 | ** |
| LnSize | -4,69549 | 0,866396 | -5,420 | <0,0001 | *** |
| LnTangible | 4,90592 | 0,964403 | 5,087 | <0,0001 | *** |
| NetLoans | -4,06382 | 0,690360 | -5,887 | <0,0001 | *** |
| ROAA | -0,287137 | 0,180896 | -1,587 | 0,1233 | |
| COVID | -0,875993 | 1,05251 | -0,8323 | 0,4120 | |
| Classification | -2,64561 | 0,762666 | -3,469 | 0,0017 | *** |

** *p*-value < 0.05, *** *p*-value < 0.01

Source: Self-elaborated from Gretl (2024).

Finally, I considered the second alternative measure of credit default risk (*BankRisk02*) with the explanatory and control variables of Equation (2). By executing the ordinary least squares (OLS) and selecting the option for considering robustness, one variable was removed from the model due to collinearity (i.e., *PostIFRS*). The obtained results are expressed in Table 7.

Table 7. OLS for *BankRisk02*

| | <i>Coefficient</i> | <i>Standard Error</i> | <i>t-test</i> | <i>p-value</i> | |
|-----------------|--------------------|-----------------------|---------------|----------------|-----|
| const | 136,850 | 20,1424 | 6,794 | <0,0001 | *** |
| PreIFRS | -5,97657 | 3,88471 | -1,538 | 0,1348 | |
| IFRSRollout | -6,11463 | 6,68398 | -0,9148 | 0,3678 | |
| Efficiency | 0,174993 | 0,314964 | 0,5556 | 0,5827 | |
| GDP | -0,131321 | 0,984697 | -0,1334 | 0,8948 | |
| IncomeDiversity | -11,0880 | 2,31699 | -4,786 | <0,0001 | *** |
| LnSize | -16,6156 | 6,98925 | -2,377 | 0,0243 | ** |
| LnTangible | 15,3892 | 7,81931 | 1,968 | 0,0587 | * |
| NetLoans | -15,9553 | 6,03806 | -2,642 | 0,0131 | ** |
| ROAA | 0,299384 | 0,348146 | 0,8599 | 0,3969 | |
| COVID | -3,06570 | 9,70116 | -0,3160 | 0,7543 | |
| Classification | -10,7554 | 6,79618 | -1,583 | 0,124 | |

** p -value < 0.05, *** p -value < 0.01

Source: Self-elaborated from Gretl (2024).

However, the three models cannot be accepted by the absence of normality of the residuals (p -value = 0.00) (see Figure 7, 8, and 9). Nevertheless, since my model did not meet this criterion, the low R-squared model cannot be accepted (as confirmed by the box plots with outliers for the three measures in Figures 10, 11, and 12).

6.4 Selection of the most suitable model

In agreement with Dougherty (2011), since I worked on a random sample, it was necessary to verify which model was the most adequate for my analysis. To begin with, I conducted the random-effect (RE) model (see Table 8).

Table 8. Random-effect model

| | <i>Coefficient</i> | <i>Standard Error</i> | <i>z-test</i> | <i>p-value</i> | |
|-----------------|--------------------|-----------------------|---------------|----------------|-----|
| const | 0,0770922 | 0,0217052 | 3,552 | 0,0004 | *** |
| PreIFRS | 0,0299488 | 0,00523614 | 5,720 | <0,0001 | *** |
| IFRSRollout | 0,0130680 | 0,00400511 | 3,263 | 0,0011 | *** |
| Efficiency | 0,000352712 | 0,000235635 | 1,497 | 0,1344 | |
| GDP | -0,000437362 | 0,000672870 | -0,6500 | 0,5157 | |
| IncomeDiversity | 0,00847664 | 0,00457425 | 1,853 | 0,0639 | * |
| LnSize | -0,0348334 | 0,00728539 | -4,781 | <0,0001 | *** |
| LnTangible | 0,0366102 | 0,00817072 | 4,481 | <0,0001 | *** |
| NetLoans | -0,0253951 | 0,00566798 | -4,480 | <0,0001 | *** |
| ROAA | -0,00218725 | 0,00151867 | -1,440 | 0,1498 | |
| COVID | -0,0132897 | 0,00782204 | -1,699 | 0,0893 | * |
| Classification | -0,0228780 | 0,00622165 | -3,677 | 0,0002 | *** |

* p -value < 0.10, ** p -value < 0.05, *** p -value < 0.01

Source: Self-elaborated from Gretl (2024).

Hence, by conducting the Durbin-Wu-Hausman test, as the p -value was smaller than 0.05 (p -value = 0.00), the fixed-effect model (FE) is more appropriate than the RE. Then, I executed the Breusch-Pagan test, to analyze if the RE is more suitable than the OLS. However, the p -value was greater than 0.05 (p -value = 0.56083). Consequently, I had to consider the OLS test because of its better fit for my model.

6.5 Kendall's Tau correlation

As the three models did not display normality of the residuals, I conducted another correlation analysis considering Kendall's Tau correlation for non-parametric tests. This measure is more efficient and robust rather than the Spearman correlation (Croux & Dehon, 2010), another test widely used for non-parametric tests.

The obtained results are expressed in Figure 13. I considered the cutoff values for Kendall's Tau correlation based on Schober et al. (2018). I interpreted the cutoff values based on Schober et al. (2018). Overall, the correlation matrix evidences weak correlations, suggesting that no variables directly influence the measures of credit default risk for banks (*BankRisk*, *BankRisk01*, and *BankRisk02*). However, there are moderate correlations between *Efficiency* and *ROAA* (-0.367***), *LnSize* and *ROAA* (-0.320***), and *LnTangible* and *ROAA* (-0.268***). Finally, in line with the correlation matrix executed in Section 6.2, *LnSize* and *LnTangible* present very strong correlation (0.860***).

Figure 13. Kendall’s Tau correlation matrix

| | BankRisk | BankRisk01 | BankRisk02 | Efficiency | GDP | IncomeDiversity | LnSize | LnTangible | NetLoans | ROAA |
|-----------------|------------|------------|------------|------------|----------|-----------------|------------|------------|----------|------|
| BankRisk | — | | | | | | | | | |
| BankRisk01 | 0.801 *** | — | | | | | | | | |
| BankRisk02 | 0.010 | 0.067 | — | | | | | | | |
| Efficiency | 0.006 | 0.043 | -0.061 | — | | | | | | |
| GDP | 0.013 | 0.001 | 0.075 | -0.028 | — | | | | | |
| IncomeDiversity | 0.070 | 0.016 | -0.115 ** | -0.194 *** | 0.115 ** | — | | | | |
| LnSize | -0.173 *** | -0.076 | 0.016 | 0.084 * | -0.022 | -0.017 | — | | | |
| LnTangible | -0.116 ** | -0.037 | 0.036 | 0.062 | -0.038 | -0.022 | 0.860 *** | — | | |
| NetLoans | 0.176 *** | -0.015 | -0.169 *** | -0.070 | -0.004 | 0.141 *** | -0.116 ** | -0.076 | — | |
| ROAA | -0.119 ** | -0.174 *** | 0.106 ** | -0.367 *** | 0.062 | 0.003 | -0.320 *** | -0.268 *** | 0.048 | — |

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

Source: jamovi (2024).

6.6 Wilcoxon test

As the model does not present the normality of the residuals, I conducted the Wilcoxon test, a non-parametric test used to compare the median of paired data (King et al., 2018). To execute this test, I used Real Statistics from Excel, a software package oriented to statistical analyses in Excel (Real Statistics, n.d.). I tested the three measures. To interpret the results, I considered the *p*-exact of two-tails since the sample size is small (n = 30). If the *p*-exact is smaller than 0.05, it is statistically significant, and the results were significant for two out of three measures, namely *BankRisk* and *BankRisk01*, indicating a significant decrease in the credit default risk for banks post-IFRS 9 mandatory adoption. Table 9 outlines the results.

Table 9. Wilcoxon test

| | <i>PreIFRS</i> | <i>PostIFRS</i> | <i>p-exact of two-tails</i> | <i>Is it statistically significant?</i> |
|-------------------|----------------|-----------------|-----------------------------|---|
| <i>BankRisk</i> | 0.020 | 0.012 | <0.01 | Yes |
| <i>BankRisk01</i> | 3.501 | 2.044 | <0.01 | Yes |
| <i>BankRisk02</i> | 60.138 | 67.326 | 0.053 | No |

Source: Self-elaborated from the Real Statistics from Excel (2024).

7. Results

The study aimed to address whether accounting quality impacts credit default risk for banks in the Eurozone. My main findings demonstrate a significant negative relationship between both variables. The results obtained from the execution of the Wilcoxon test found that both the primary measure (*BankRisk*) and the first alternative measure (*BankRisk01*) displayed a pronounced reduction in credit default risk for banks after the mandatory adoption of IFRS 9. For *BankRisk*, there was a 40% reduction in credit default risk, dropping from 0.020 to 0.012.

In parallel, for *BankRisk01*, there was a 41.62% reduction, dropping from 3.501 to 2.044. Conversely, *BankRisk02* presented a countermovement, by exhibiting an increase from 60.138 to 67.326. However, the *p*-exact of two-tails for this variable is greater than 0.05 (*p*-exact = 0.053), indicating that this variable is not statistically significant.

The results aligned with previous findings on the effect of IFRS on banks. In agreement with Kyiu and Tawiah (2023), although there is a convergence of the obtained results, they highlighted that the impact of IFRS 9 is more pronounced for banks based in countries with stronger accounting regulatory systems. According to Barth and Landsman (2010), accounting regulation settings influence bank activities because of the effect that financial reports have on their capital ratios and supervision. Despite I did not include any control variable related to institutional settings, the sound regulation system of the Eurozone may be one of the main justifications for these significant reductions post-IFRS 9 mandatory adoption.

However, Bitar et al. (2018) highlighted an opposite standpoint on accounting settings. They pointed out that strict accounting impositions by Basel III such as holding higher capital and liquidity ratios are detrimental to the efficiency and performance of banks. Similarly, but concerning the IFRS, DeFond et al. (2015) found that IFRS does not impact the bankruptcy ratios for financial firms. However, for financial firms based in countries with weak banking regulation, which is not the case in the Eurozone, IFRS may even leverage these ratios. Nevertheless, the likelihood of a bank taking on risky investments under IFRS 9 is smaller because of credit loss provisions (Novotny-Farkas, 2016).

8. Conclusions

In this study, I aimed to broaden the literature on the real effects of mandatory IFRS 9 adoption on the credit default risk for banks in the Eurozone context. As this accounting standards setting has been in force since 2018, there are few studies concentrated on understanding this financial statement. One of the first scholars that worked on this topic were Kyiu and Tawiah (2023).

Despite the crucial role played by IFRS adoption in the economy (Liu et al., 2023), previous literature has been mainly focusing on investigating to which extent IFRS enhances comparability in financial reports (Barth et al., 2012; Landsman et al., 2012; Lin et al., 2019; Conaway, 2022), as well as its impact on capital-market structure (Loureiro & Taboada, 2015; Gao et al., 2019; Liu et al., 2023). However, the banking sector has still been neglected by scholars because of its inherent complexity (Beatty & Lino, 2014).

For this reason, my research question aimed to address whether accounting quality impacts credit default risk for banks in the Eurozone. In parallel, concerning the objective, I aimed to analyze the relationship between accounting quality and credit default risk for banks. After conducting several statistical analyses and sensitivity checks, I was able to fully address my proposed hypothesis (*Accounting quality decreases the credit default risk for banks*), obtaining results in agreement with overall previous findings.

Regarding the limitations, I fully focused on articles published in Q1 journals. Although this enhances more accuracy of the overall study, the great majority of articles that were analyzed constitute an interplay among different fields such as accounting, economics, and finance. Consequently, it hampered my understanding of some topics and even deepen both the literature review and applied methodology. Additionally, because of academic knowledge, I was not able to conduct one of the most common statistical procedures conducted by previous scholars such as the difference-in-difference test (Kyiu & Tawiah, 2023; Liu et al., 2023). Further, due to the dependent, independent, and control variables, Orbis yielded a small sample of 30 bank-year observations. However, despite this small size, I executed several statistical checks to enhance the robustness of my results. Moreover, the applicability of this study is limited to the Eurozone context.

As I progressed through the literature review development, I realized that IFRS was often adopted along with concurrent institutional reforms, making it difficult to identify the real effects of isolated IFRS (Leuz & Wysocki, 2016). Accordingly, this indicates future avenues of research. I propose to analyze the moderating role of institutional settings in the relationship between IFRS 9 and banks risk from a cross-country perspective.

From an academic perspective, this study contributes to the beginning of the development of a promising line of research in accounting and finance. Further, from a practical standpoint, in conformity with Jeanjean and Stolowy (2008), the main implication of this study is to incentivize policymakers to concentrate on the improvement of institutional reforms than the harmonization of financial reports since them is likely to be more relevant for credit default risk for banks.

References

- Ball, R., & Shivakumar, L. (2015). Contractibility and Transparency of Financial Statement Information Prepared Under IFRS: Evidence from Debt Contracts Around IFRS Adoption. *Journal of Accounting Research*, 53(5), 915–963. <https://doi.org/10.1111/1475-679X.12095>
- Bank for International Settlements. *IFRS 9 and expected loss provisioning – Executive Summary*. <https://www.bis.org/fsi/fsisummaries/ifrs9.pdf>
- Barth, M., & Landsman, W. (2010). How did financial reporting contribute to the financial crisis? *European Accounting Review*, 19(3), 399–423. <https://doi.org/10.1080/09638180.2010.498619>
- Barth, M. E., Landsman, W. R., Lang, M., & Williams, C. (2012). Are IFRS-based and US GAAP-based accounting amounts comparable? *Journal of Accounting & Economics*, 54(1), 68–93. <https://doi.org/10.1016/j.jacceco.2012.03.001>
- Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, 58(2/3), 339–383. <https://doi.org/10.1016/j.jacceco.2014.08.009>
- Beck, T., & Demigurc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, 30(11), 2931–2943. <https://doi.org/10.1016/j.jbankfin.2006.05.009>
- Berger, A. N., Molyneux, P., & Wilson, J. O. S. (2020). Banks and the real economy: An assessment of the research. *Journal of Corporate Finance*, 62, 101513. <https://doi.org/10.1016/j.jcorpfin.2019.101513>
- Bhagat, S., Bolton, B., & Lu, J. (2015). Size, leverage, and risk-taking of financial institutions. *Journal of Banking & Finance*, 59, 520–537. <https://doi.org/10.1016/j.jbankfin.2015.06.018>
- Bitar, M., Pukthuanthong, K., & Walker, T. (2018). The effect of capital ratios on the risk, efficiency and profitability of banks: Evidence from OECD countries. *Journal of International Financial Markets Institutions and Money Forthcoming*, 53, 227–262. <https://doi.org/10.1016/j.intfin.2017.12.002>
- Brown, A. B. (2016). Institutional Differences and International Private Debt Markets: A Test Using Mandatory IFRS Adoption. *Journal of Accounting Research*, 54(3), 679–723. <https://doi.org/10.1111/1475-679X.12111>

- Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics*, 54(1), 1–18. <https://doi.org/10.1016/j.jacceco.2012.04.002>
- Conaway, J. K. (2022). Has Global Financial Reporting Comparability Improved? *Contemporary Accounting Research*, 39(4), 2825–2860. <https://doi.org/10.1111/1911-3846.12796>
- Croux, C., & Dehon, C. (2010). Influence functions of the Spearman and Kendall correlation measures. *Statistical Methods & Applications*, 19, 497–515. <https://doi.org/10.1007/s10260-010-0142-z>
- Dávila, E., & Walther, A. (2020). Does size matter? Bailouts with large and small banks. *Journal of Financial Economics*, 136(1), 1–22. <https://doi.org/10.1016/j.jfineco.2019.09.005>
- DeFond, M., Hu, X., Hung, M., & Li, S. (2011). The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting & Economics*, 51(3), 240–258. <https://doi.org/10.1016/j.jacceco.2011.02.001>
- DeFond, M. L., Hung, M., Li, S., & Li, Y. (2015). Does mandatory IFRS adoption affect crash risk? *The Accounting Review*, 90(1), 265–299. <https://doi.org/10.2308/accr-50859>
- Dougherty, C. (2011). *Introduction to Econometrics*. Oxford: Oxford University Press.
- Elnahass, M., Trinh, V. Q., & Li, T. (2021). Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets, Institutions and Money*, 72, 101322. <https://doi.org/10.1016/j.intfin.2021.101322>
- European University Institute. (n.d.). *Orbis Europe - European Company Data*. Retrieved from <https://www.eui.eu/Research/Library/ResearchGuides/Economics/Statistics/DataPortal/OrbisEurope>
- Gao, P., Jiang, X., & Zhang, G. (2019). Firm value and market liquidity around the adoption of common accounting standards. *Journal of Accounting and Economics*, 68(1), 101220. <https://doi.org/10.1016/j.jacceco.2018.11.001>
- Gomaa, M., Kanagaretnam, K., Mestelman, S., & Shehata, M. (2019). Testing the efficacy of replacing the incurred credit loss model with the expected credit loss model. *European Accounting Review*, 28(2), 309–334. <https://doi.org/10.1080/09638180.2018.1449660>

- Gretl. (n.d.) *Gretl*. Retrieved from <https://gretl.sourceforge.net/>
- HSBC Holdings plc. *Report on Transition to IFRS 9 'Financial Instruments'*. <file:///C:/Users/Lenovo/Downloads/180227-report-on-transition-to-ifs9-financial-instruments-1-january-2018.pdf>
- International Monetary Fund. (2024). *World Economic Outlook (April 2024)*. Retrieved from <https://www.imf.org/external/datamapper/datasets/WEO>
- Isidro, H., Nanda, D., & Wysocki, P. (2019). On the Relation between Financial Reporting Quality and Country Attributes: Research Challenges and Opportunities. *The Accounting Review*. <https://doi.org/doi:10.2308/accr-52607>
- jamovi. (n.d.) *jamovi*. Retrieved from <https://www.jamovi.org/>
- Jeanjean, T., & Stolowy, H. (2008). Do accounting standards matter? An exploratory analysis of earnings management before and after IFRS adoption. *Journal of Accounting and Public Policy*, 27(6), 480–494. <https://doi.org/10.1016/j.jaccpubpol.2008.09.008>
- Judge, W., Li, S., & Pinsker, R. (2010). National adoption of international accounting standards: An institutional perspective. *Corporate Governance*, 18(3), 161–174. <https://doi.org/10.1111/j.1467-8683.2010.00798.x>
- Kim, J-B., Li, L., Lu, L. Y., & Yu, Y. (2016). Financial statement comparability and expected crash risk. *Journal of Accounting and Economics*, 61(2–3), 294–312. <https://doi.org/10.1016/j.jacceco.2015.12.003>
- Kim, J-B., Simunic, D. A., Stein, M. T., & Yi, C. H. (2011). Voluntary Audits and the Cost of Debt Capital for Privately Held Firms: Korean Evidence. *Contemporary Accounting Research*, 28(2), 585–615. <https://doi.org/10.1111/j.1911-3846.2010.01054.x>
- Kim, J.-B., Tsui, J. S. L., & Yi, C. H. (2011). The voluntary adoption of International Financial Reporting Standards and loan contracting around the world. *Review of Accounting Studies*, 16(4), ISSN 1380–6653. <https://doi.org/10.1007/s11142-011-9148-5>
- King, B. M., Rosopa, P. J., & Minium, E. W. (2018). *Statistical reasoning in the behavioral sciences*. New Jersey, NJ: John Wiley & Sons.

- Knight, G. A., & Kim, D. (2009). International business competence and the contemporary firm. *Journal of International Business Studies*, 40(2), 255–273. <https://doi.org/10.1057/palgrave.jibs.8400397>
- Kyiu, A., & Tawiah, V. (2023). IFRS 9 implementation and bank risk. *Accounting Forum*, 1–25. <https://doi.org/10.1080/01559982.2023.2233861>
- Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics*, 85(2), 331–367. <https://doi.org/10.1016/j.jfineco.2005.06.001>
- Lamoreaux, P. T., Michas, P. N., & Schultz, W. L. (2015). Do accounting and audit quality affect World Bank lending? *Accounting Review*, 90(2), 703–738. <https://doi-org.sire.ub.edu/10.2308/accr-50865>
- Landsman, W. R., Maydew, E. L., & Thornock, J. R. (2012). The information content of annual earnings announcements and mandatory adoption of IFRS. *Journal of Accounting & Economics*, 53(1–2), 34–54. <https://doi.org/10.1016/j.jacceco.2011.04.002>
- Leuz, C., & Wysocki, P. (2016). The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research*, 54(2), 525–622. <https://doi.org/10.1111/1475-679X.12115>
- Lin, S., Riccardi, W., & Wang, C. (2019). Relative Effects of IFRS Adoption and IFRS Convergence on Financial Statement Comparability. *Contemporary Accounting Research*, 36(2), 588–628. <https://doi.org/10.1111/1911-3846.12475>
- Liu, J., Shi, W., Zeng, C., & Zhang, G. (2023). Does Public Firms' Mandatory IFRS Reporting Crowd Out Private Firms' Capital Investment? *Journal of Accounting Research*, 61(4), 1263–1312. <https://doi.org/10.1111/1475-679X.12494>
- López-Espinosa, G., Ormazabal, G., & Sakasai, Y. (2021). Switching from Incurred to Expected Loan Loss Provisioning: Early Evidence. *Journal of Accounting Research*, 59(3), 757–804. <https://doi.org/10.1111/1475-679X.12354>
- Loureiro, G., & Taboada, A. G. (2015). Do Improvements In the Information Environment Enhance Insiders' Ability to Learn from Outsiders? *Journal of Accounting Research*, 53(4), 863–905. <https://doi.org/10.1111/1475-679X.12082>

- Novotny-Farkas, Z. (2016). The interaction of the IFRS 9 expected loss approach with supervisory rules and implications for financial stability. *Accounting in Europe*, 13(2), 197–227. <https://doi.org/10.1080/17449480.2016.1210180>
- Real Statistics. (n.d.) *Welcome*. Retrieved from <https://real-statistics.com/>
- PwC. (n.d.). *IFRS 9, Financial Instruments*. <https://www.pwc.co.uk/who-we-are/regions/london/PwC-IFRS9-understanding-the-basics.pdf>
- S&P Dow Jones Indices. *Rotating Australian Cyclical and Defensive Sectors Over Global Economic Cycles*. Retrieved from <https://www.indexologyblog.com/tag/cyclical-sectors/>
- Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia and Analgesia*, 126(5), 1763–1768. <https://doi.org/0.1213/ANE.0000000000002864>
- VOSviewer. (n.d.). *Highlights*. Retrieved from <https://www.vosviewer.com/features/highlights>

Appendix

Table 1. Selection of articles

| <i>Database</i> | <i>Scopus</i> | <i>Amount of papers in each applied filter</i> |
|--------------------------------------|---|--|
| Article title, Abstract, Keywords | IFRS | 4,472 |
| Year | 2005–2024 | 4,430 |
| Subject area | Business, Management, and Accounting | 3,287 |
| Document type | Article | 2,760 |
| Language | English | 2,623 |
| Source type | Journal | 2,602 |
| Source title | <i>Accounting Review, Review Of Accounting Studies, Contemporary Accounting Research, Journal Of Accounting Research, and Journal Of Accounting And Economics</i> | 108 |
| Publication stage | Final | 108 |
| Keywords | <i>IFRS, IFRS Adoption, International Financial Reporting Standards (IFRS), International Reporting Standards</i> | 63 |
| Total of articles used in this study | 14 | 14 |

Source: Self-elaborated (2024).

Table 3. List of banks

| <i>Countries</i> | <i>Banks</i> |
|------------------|---------------------------|
| Austria | Erste Group Bank |
| | Raiffeisen Bank |
| Belgium | KBC Groupe |
| Croatia | Podravska Banka |
| Cyprus | Hellenic Bank |
| Estonia | AS LHV Group |
| France | Crédit Agricole |
| | Société Générale |
| Germany | Deutsche Bank |
| | MLP SE |
| Greece | Piraeus |
| Italy | Banca Generali |
| | Banca IFIS |
| | Banca Monte Dei Paschi |
| | Banca Popolare di Sondrio |
| | Banca Sistema |
| | BPER |
| | Credito Emiliano |
| | Intesa Sanpaolo |
| | Mediobanca |
| | Lithuania |
| Portugal | Banco Comercial Português |
| Slovak Republic | Tatra Bank |
| Slovenia | Nova Ljubljanska Banka |
| Spain | Banco Sabadell |
| | Bankinter |
| | BBVA |
| | Santander |
| The Netherlands | ABN AMRO |
| | ING |

Source: Self-elaborated (2024).

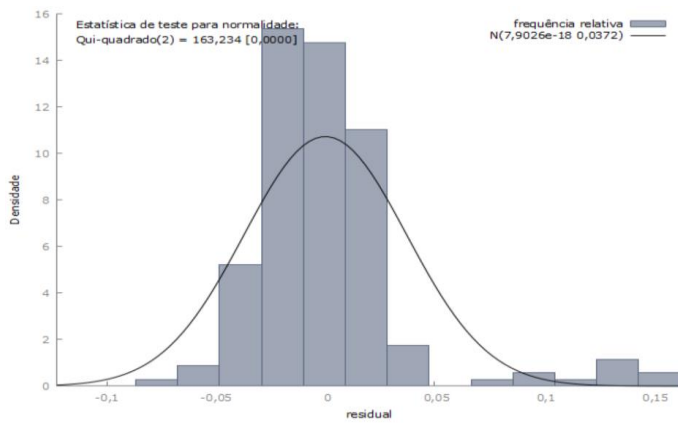
Table 4. Variables definition

| <i>Variables name</i> | <i>Descriptions</i> | <i>References</i> |
|-------------------------------------|--|--------------------------|
| <i>Dependent variables</i> | | |
| BankRisk* | Loan loss reserves/Total assets | Bitar et al. (2018) |
| BankRisk02** | Loan loss reserves/Gross loans | Bitar et al. (2018) |
| BankRisk03** | Loan loss reserves/Impaired loans | Bitar et al. (2018) |
| <i>Independent variables</i> | | |
| PreIFRS | Value of 1 for the pre-IFRS 9 period and 0 otherwise | Kyiu and Tawiah (2023) |
| IFRSRollout | Value of 1 for the IFRS 9 rollout period and 0 otherwise | Kyiu and Tawiah (2023) |
| PostIFRS | Value of 1 for the post-IFRS 9 period and 0 otherwise | Kyiu and Tawiah (2023) |
| <i>Control variables</i> | | |
| Efficiency | Bank overheads | Bitar et al. (2018) |
| GDP | Growth in GDP | Kyiu and Tawiah (2023) |
| IncomeDiversity | Banks diversification between lending and non-lending activities | Laeven and Levine (2007) |
| | | Bitar et al. (2018) |
| LnSize | Natural logarithm of bank assets | Kyiu and Tawiah (2023) |
| | | Liu et al. (2023) |
| LnTangible | Natural logarithm of tangible equity | Bitar et al. (2018) |
| NetLoans | Loan portfolio diversification | Bitar et al. (2018) |
| | | Kyiu and Tawiah (2023) |
| ROAA | Return on average assets | Liu et al. (2023) |
| Σ Classification | Value 1 for investment banks and 0 otherwise | Bhagat et al. (2015) |
| Σ COVID | Value of 1 for the COVID-19 period and 0 otherwise | Elnahass et al. (2021) |

* Primary measure ** Robustness measure

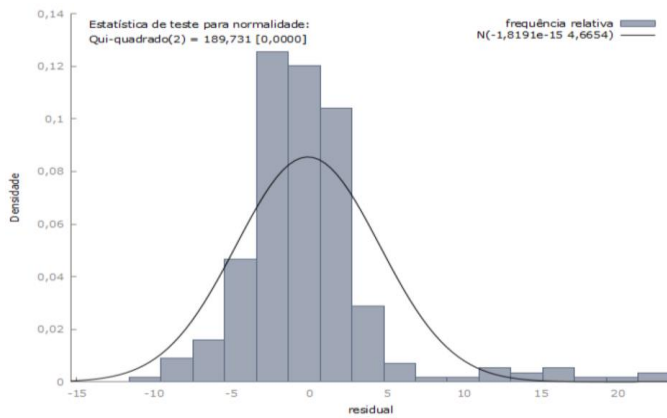
Source: Self-elaborated (2024).

Figure 7. Statistical test for normality for *BankRisk*



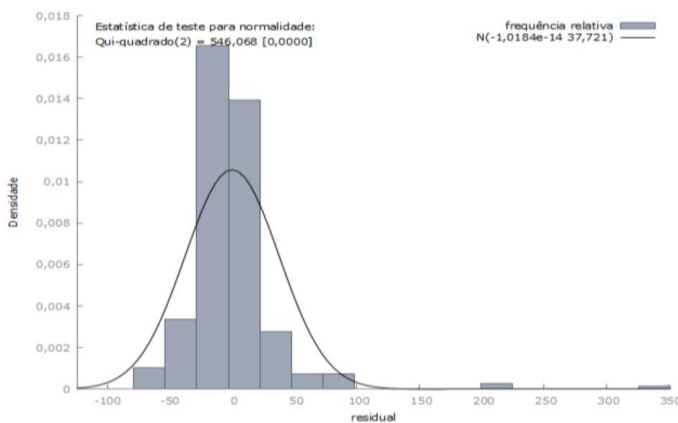
Source: Gretl (2024).

Figure 8. Statistical test for normality for *BankRisk01*



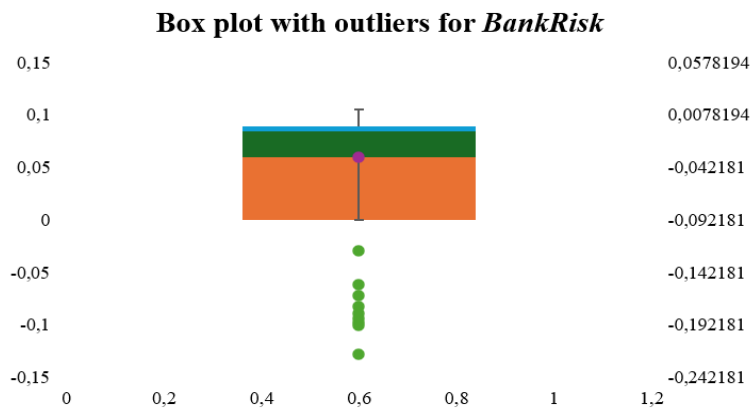
Source: Gretl (2024).

Figure 8. Statistical test for normality for *BankRisk02*



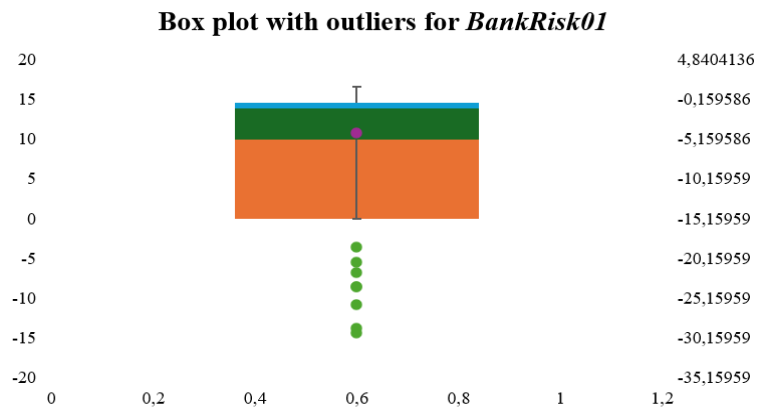
Source: Gretl (2024).

Figure 10. Box plot with outliers for *BankRisk*



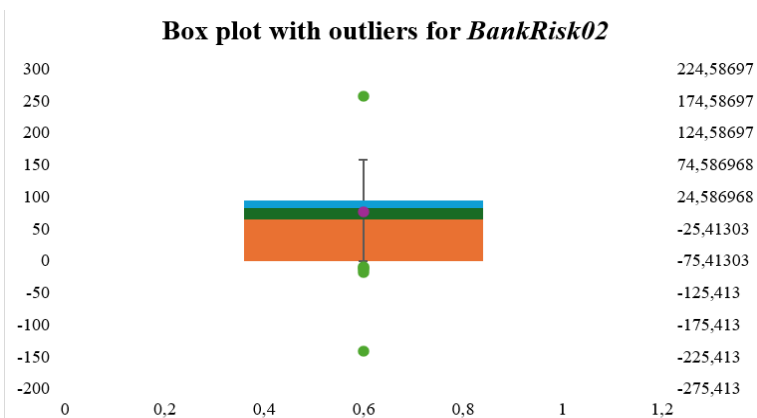
Source: Real Statistics from Excel (2024).

Figure 11. Box plot with outliers for *BankRisk01*



Source: Real Statistics from Excel (2024).

Figure 12. Box plot with outliers for *BankRisk02*



Source: Real Statistics from Excel (2024).