Vaasan yliopisto
UNIVERSITY OF VAASA

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IFRS 9 Impairment Provisioning Determinants

Evidence from Public Data of European Banks During 2018Q4 – 2024Q2

School of Accounting and Finance
Master's Thesis
Economics Master's Program

Vaasa 2025

UNIVERSITY OF VAASA			
School of Accounting and Finance			
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Title of the thesis:	IFRS 9 Impairment Provisioning Determinants: Evidence from Public Data of European Banks During 2018Q4 – 2024Q2		
Degree:	Master of Science in Economics and Business Administration		
Discipline:	Master's Programme in Economics		
Supervisor:	Panu Kalmi		
Year:	2025	**Pages:**	80

ABSTRACT:

Banks' ability to absorb loan losses and maintain financial stability depends on timely and adequate loan loss provisioning. In 2018, the IFRS 9 accounting standard introduced a forward-looking expected credit loss (ECL) approach to encourage earlier recognition of credit losses and reduce procyclicality. However, the framework allows considerable discretion, which may give rise to variation in provisioning practices across banks. This study investigates the determinants of banks' impairment provisions under the IFRS 9 regime, with particular attention to discretionary practices such as income smoothing, capital management, and delayed loss recognition, as well as structural outcomes like procyclicality.

The analysis applies an empirical model to a panel of European banks covering the period from 2018:Q4 to 2024:Q2. The study is based on publicly available data from the European Banking Authority's EU-wide Transparency Exercise, comprising more than 2,200 bank-quarter observations across 127 banks in 27 countries. The sample spans a period of significant macro-financial change, including the post-pandemic shift to a rising interest rate environment. This allows for timely examination of the provisioning behaviour under diverse economic conditions. The model relates loan loss provisions to factors reflecting earnings, capital adequacy, credit risk, and macroeconomic conditions, allowing for the assessment of the key hypothesized behaviours.

The empirical findings largely align with patterns reported in earlier studies. Provisioning is still used to smooth earnings, as indicated by a significant positive relationship between pre-impairment income and provisions. Unlike in earlier studies, no evidence is found that banks with weaker capital positions provision less, suggesting an absence of capital management effects. Loss recognition remains delayed, with provisions increasing significantly when loans become non-performing. In addition, provisioning under IFRS 9 remains procyclical, despite its forward-looking design. These results posit that discretionary provisioning practices persist under IFRS 9.

The findings carry important policy implications. They underscore the continued need for supervisory oversight to ensure that banks' use of discretion in provisioning does not undermine transparency or financial stability. Improved disclosure and greater consistency in provisioning practices could help strengthen market discipline and comparability across institutions. By offering timely and comprehensive evidence, this study updates the literature on IFRS 9 impairment behaviour and provides a basis for evaluating the effectiveness of the ECL framework in diverse macro-financial conditions.

AVAINSANAT: Banks, IFRS 9, Expected Credit Losses, Impairment Provisions, Loan Loss Provisions, Discretion, Lending, Procyclicality

VAASAN YLIOPISTO
School of Accounting and Finance
Tekijä: Jesse Puuska
Tutkielman nimi: IFRS 9 Impairment Provisioning Determinants: Evidence from Public Data of European Banks During 2018Q4 – 2024Q2
Tutkinto: Kauppatieteiden maisteri
Oppiaine: Taloustieteen maisteriohjelma
Ohjaaja: Panu Kalmi
Valmistumisvuosi: 2025 **Sivumäärä:** 80

TIIVISTELMÄ:
Riittävä ja oikea-aikainen varautuminen luottotappioihin tukee pankkien kykyä kestää luottotappiot ja ylläpitää vakavaraisuutta. IFRS 9 -tilinpäätösstandardi toi vuonna 2018 käyttöön ennakoivan odotettuihin luottotappioihin perustuvan lähestymistavan (ECL), jonka tavoitteena oli luottotappioiden aikaisempi kirjaaminen ja vähenevä myötäsyklisyys. IFRS 9 antaa pankeille kuitenkin runsaasti harkinnanvaraa, mikä voi johtaa eroihin varauskäytännöissä. Tässä tutkimuksessa selvitetään pankkien arvonalentumisvarausten määräytymiseen vaikuttavia tekijöitä. Erityinen huomio kiinnitetään harkinnanvaraisiin käytäntöihin, kuten tuloksen hallintaan, pääoman hallintaan ja odotettujen tappioiden viivästyneeseen kirjaamiseen sekä rakenteellisiin ilmiöihin, kuten myötäsyklisyyteen.

Tutkimuksessa sovelletaan empiiristä mallia eurooppalaisten pankkien aineistoon ajalta 2018:Q4–2024:Q2. Aineisto perustuu Euroopan pankkiviranomaisen (EBA) julkisiin Transparency Exercise -tietoihin ja kattaa yli 2 200 havaintoa 127 pankista 27 maassa. Tarkasteltava jakso kattaa merkittäviä muutoksia toimintaympäristössä, kuten pandemian jälkeisen korkojen nousun, mahdollistaen ajantasaisen analyysin erilaisissa makrotaloudellisissa olosuhteissa. Mallissa luottotappiovaraukset yhdistetään pankkien tulokseen, vakavaraisuuteen, luottoriskiin ja talouskehitykseen, mikä mahdollistaa keskeisten käyttäytymisoletusten testaamisen.

Empiiriset havainnot ovat pitkälti linjassa aiempien tutkimusten tulosten kanssa. Varauksia käytetään edelleen tuloksen hallintaan, mistä osoituksena on merkittävä positiivinen yhteys arvonalentumiskirjauksia edeltävän tuloksen ja varausmäärien välillä. Aiemmista tutkimuksista poiketen tässä analyysissä ei havaittu todisteita pääoman hallinnasta. Tappioiden kirjaaminen on yhä viivästynyttä ja varaukset kasvavat merkittävästi lainoja luokiteltaessa järjestämättömiksi. IFRS 9:n ennakoivasta luonteesta huolimatta luottotappiovaraukset ovat edelleen myötäsyklisiä. Nämä havainnot viittaavat siihen, että harkinnanvaraiset varauskäytännöt ovat jatkuneet.

Tuloksilla on tärkeitä politiikkavaikutuksia. Ne korostavat jatkuvan viranomaisvalvonnan tarvetta sen varmistamiseksi, että pankkien harkinnanvarainen varautuminen ei heikennä läpinäkyvyyttä tai rahoitusvakautta. Tietojen avoimuuden parantaminen ja varauskäytäntöjen yhtenäistäminen voisivat osaltaan vahvistaa markkinakuria ja lisätä vertailukelpoisuutta pankkien välillä. Tarjoamalla ajankohtaista ja kattavaa näyttöä tämä tutkimus päivittää IFRS 9:n mukaista arvonalentumiskäyttäytymistä koskevaa kirjallisuutta ja luo perustan ECL-kehikon tehokkuuden arvioinnille erilaisissa makrotaloudellisissa olosuhteissa.

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Contents

Figures

Tables

1 Introduction

The International Accounting Standards Board (IASB) introduced the new International Financial Reporting Standard 9 - Financial Instruments (IFRS 9) Expected Credit Loss (ECL) framework in 2014 and it was deployed in January 2018 (Bank for International Settlements, 2017, p. 1), marking a major shift in accounting practices for financial institutions. The framework provides guidelines on classifying and measuring financial assets for recognizing expected credit losses (Bank for International Settlements, 2017, p. 1–2). Compared to the previous incurred loss (IL) framework, IFRS 9 requires banks to recognize ECL earlier and more proactively (Bank for International Settlements, 2017, p. 1–2).

Behn and Cyril (2023) emphasize that adequate and timely credit risk provisioning is crucial for banks to absorb losses without endangering their solvency or financial system stability. It also improves risk transparency for investors and supervisors, enhancing market discipline and supporting effective oversight. Furthermore, they highlight that sufficient provisioning during expansions can reduce banking sector procyclicality and support lending during downturns. In line with these concerns, Behn and Cyril (2023) and Cohen and Edwards (2017) explain that the ECL framework was designed to address the key failings of earlier models, which were widely seen as producing provisions that came too late and were too small during the 2007–2008 financial crisis.

Despite its aim to improve timeliness and transparency, IFRS 9 grants banks substantial discretion in estimating provisions (Behn & Cyril, 2023, p. 13–14). While this flexibility helps capture novel risks (European Central Bank, 2024a, p. 3), it also raises concerns about opportunistic behaviours, such as earnings and capital management (Behn & Cyril, 2023, p. 6–7). Supervisory authorities have been actively monitoring the evolution of these discretionary elements and have expressed concerns in recent assessments (e.g., European Banking Authority, 2023; European Central Bank, 2024a). Provisioning practices have also been extensively examined historically in academic literature (Beatty & Liao, 2014, p. 339–341).

Novotny-Farkas et al. (2024) analyse banks' impairment provisioning practices under IFRS 9, especially finding evidence of for example income smoothing, lower provisioning by weakly capitalized banks, delayed loss recognition, and procyclicality, which to some extent overlap with concerns raised in recent supervisory assessments.

Motivated by these institutional concerns and empirical findings, this study investigates banks' impairment provisioning behaviour over a more recent and extended period, using the methodology and regression model of Novotny-Farkas et al. (2024). Since the ECL framework was only introduced in 2018, it remains relatively new, and the number of empirical studies on provisioning behaviour under this standard is still limited. As a result, research based on newer and broader datasets has inherent value, not only by providing fresh evidence but also by validating earlier findings, which were necessarily derived from shorter time periods and smaller samples. This study contributes to the literature by testing the robustness of prior results in a period characterized by a distinct macroeconomic environment. A further contribution is its exclusive reliance on publicly available data, which enhances transparency and promotes replicability.

1.1 Research Questions

This study seeks to validate the findings of Novotny-Farkas et al. (2024) on banks' loan loss provisioning practices under the IFRS 9 ECL framework. Specifically, it examines whether the evidence of income smoothing, capital management, delayed loss recognition, and procyclicality observed in their sample (2018Q4–2022Q2) continues to hold in the extended sample used in this study, covering a different economic environment up to 2024Q2. This research aligns with the authors' call for further investigation into the long-term effects of the ECL model as additional data become available (Novotny-Farkas et al., 2024, p. 32).

To address these aims, the study applies the empirical strategy developed by Novotny-Farkas et al. (2024) and analyses an expanded dataset constructed entirely from publicly available sources. The analysis focuses on four core research questions that target the main dimensions of provisioning behaviour highlighted in the literature: the association between income before impairments and provisioning (RQ1), the influence of capital adequacy on provisioning decisions (RQ2), the responsiveness of provisioning to deteriorating credit quality, with an emphasis on delayed expected loss recognition (RQ3), and the relationship between provisioning and macroeconomic conditions, reflecting potential procyclicality (RQ4). These questions are formalized as follows:

RQ1: Does income before impairments have a positive association with impairment provisioning?

RQ2: Is lower regulatory capital adequacy associated with lower levels of impairment provisioning?

RQ3: Are increases in non-performing exposures positively associated with impairment provisioning?

RQ4: Does impairment provisioning behaviour exhibit a negative association with macroeconomic conditions?

1.2 Thesis Structure

The thesis is divided into five interconnected chapters, each building on the preceding one to provide a comprehensive examination of discretionary behaviour in banks' impairment provisioning under IFRS 9 framework.

The thesis begins with the introduction, which presents the research background, motivation, and objectives. It formulates the research questions focusing on income smoothing, capital management, delayed loss recognition, and procyclicality in impairment provisioning, and outlines the contribution of the study within the broader academic and regulatory context.

Following this, in Section 2 the theoretical and regulatory foundations are presented. This chapter discusses the IFRS 9 accounting standard, including the three-stage impairment framework, the application of statistical models and management overlays, and the supervisory expectations that influence provisioning practices. It establishes the conceptual groundwork necessary to understand the empirical analysis.

The discussion then moves to the literature review in Section 3, which situates the study within existing academic research. The chapter synthesizes prior findings related to the four central themes of the thesis and clarifies the theoretical mechanisms that underpin empirical hypotheses. This review provides the intellectual framework for the subsequent empirical work.

Building on the theoretical insights, the empirical analysis in Section 4 details the research design, including data sources, sample construction, variable selection, and methodological approach. It explains how the study replicates and extends the work of Novotny-Farkas et al. (2024), using publicly available data over an extended period from 2018Q4 to 2024Q2. The empirical results are presented and critically assessed, with particular attention to their consistency across time and their robustness.

The thesis concludes in Section 5 that synthesizes the main findings, reflects on their theoretical and policy implications, and proposes directions for future research. Overall, the structure of the thesis ensures a logical progression from the formulation of research questions to their empirical investigation and final reflection, allowing the reader to follow the development and resolution of the central themes of the study.

2 IFRS 9 and Impairment Provisioning

This section introduces the principles and practices of impairment provisioning under IFRS 9. It explains the key concepts behind loan loss and impairment provisioning, the shift to the ECL framework, and how banks estimate provisions in practice. The section also covers the main tools used for ECL estimation, such as statistical models and management overlays, and highlights important regulatory considerations. Together, these insights establish the foundation for understanding the empirical analysis conducted later in this thesis.

2.1 Impairment Provisioning

Loan loss provisioning entails allocating a proportion of profits to cover potential future loan defaults (Choudhry, 2018, pp. 89–93). In practice, it means that a part of a bank's capital is earmarked as a buffer to absorb losses arising from defaulted loans. Consequently, provisioning reduces the bank's after-tax profits. Additionally, provisions affect prudential capital ratios (European Central Bank, 2024b, pp. 2).

Impairment provisioning is conceptually very similar to loan loss provisioning, and the two terms are often used interchangeably in academic literature. For example, Novotny-Farkas et al. (2024) use both terms in this manner when referring to the recognition of expected credit losses. However, impairment provisioning is a broader term, requiring recognition of credit losses also on other types of financial assets beyond loans (Bank for International Settlements, 2017).

In this thesis, the term impairment provisioning will be used primarily, as it aligns with the terminology adopted in IFRS 9 and more precisely reflects the nature of the data employed in the analysis. However, in discussions where the distinction between impairment provisioning and loan loss provisioning is relevant, the terminology used in the original source will be retained to accurately reflect the authors' conceptual framing.

2.2 IFRS 9 Accounting Standard

The IASB issued the IFRS 9 accounting standard in 2014, introducing a principles-based ECL framework for the recognition of impairment on financial assets (Bank for International Settlements, 2017). The new accounting standard was later enforced in 2018, and it provides guidance on how entities should classify and measure financial assets and liabilities.

According to Bank for International Settlements (2017), the ECL framework is applied for financial assets held Amortized Cost (AC), as well as to certain other instruments such as lease receivables, loan commitments, and financial guarantee contracts. For other financial assets, there is no need to calculate ECL as under Fair Value Through Profit or Loss (FVPL) the fair value already changes through profit and loss and for Fair Value Through Other Comprehensive Income (FVOCI), there is no credit risk.

According to Kvaal et al. (2023), empirical evidence suggests that the IFRS 9 classification guidance and criteria have had a limited impact on banks' balance sheet structure. As the focus of this study is on the impairment component of financial assets' measurement, classification criteria are not examined in detail and are not expected to significantly affect the analysis of impairment provisioning.

When estimating the ECL for impairment provisioning, the key distinction between the IFRS 9's ECL framework and the prior IL frameworks lies in their treatment of time. Whereas the prior frameworks required banks to recognize credit losses only when objective evidence of impairment had emerged, the new ECL framework mandates that banks account for expected losses considering forecasts about risks realizing in future (Bank for International Settlements, 2017). Moreover, the IFRS 9 approach necessitates that banks incorporate past events, current conditions, and forward-looking information in calculating ECL (Bank for International Settlements, 2017).

Under IFRS 9 impairments are recognized through a three-stage approach, where provisions increase as credit risk worsens (Bank for International Settlements, 2017).

According to the European Banking Authority (EBA)'s Risk Dashboard (2024b), most of the total gross loans and advances are sorted to stage 1 (88.1 %[1]). These are newly originated or purchased performing loans is without significant increase in credit risk (SICR) (2023, pp. 10–11). For these financial assets, ECL is calculated as the result of multiplying Probability of Default (PD) one year (12-months) ahead of the expected lifetime loss given default.

The second largest proportion (9.6 %) of gross loans and advances is sorted to stage 2 (European Banking Authority, 2024b). Behn and Cyril (2023, p. 10–11) explain that a loan is moved to stage 2 if is encounters SICR according to the bank's criteria. For these loans, ECL is calculated as the result of multiplying the PD loan lifetime ahead by the expected lifetime loss given default. Since the probability of defaulting at any point in the future is inherently a lot higher than defaulting during the next 12-months, it can be concluded that the provisioning for stage 2 loans can be significantly higher than for stage 1 loans.

Finally, the smallest (2.2 %) proportion of gross loans and advances is sorted to stage 3 (European Banking Authority, 2024b). These loans are like those reported under the IL framework in an essence that it considers loans with objective indications of credit impairment (Behn & Cyril, 2023, p. 11). For these loans the lifetime ECL is calculated similarly to stage 2 loans (Behn & Cyril, 2023, p. 10–11). Notably, as the loans in stage 3 are already credit impaired, the lifetime probability of default can be significantly higher. More precisely, the lifetime PD is often being 100 % due to strong overlap between IFRS 9 definition of credit-impaired and prudential definition of default if the loan is considered defaulted (Behn & Cyril, 2023, p. 11). Consequently, the resulting ECLs are significantly higher for stage 3 loans than for stage 2, as is presented later.

[1] Figures from Q4 2023

For stage 1 and 2 loans, interest revenue is calculated on the loan's gross carrying amount (Bank for International Settlements, 2017). ECL is not deducted. For stage 3 loans, interest revenue is calculated after deducting the ECL, resulting in lower reported interest income.

The classification logic and ECL calculation methods described above are summarised in Table 1. The table provides a consolidated overview of the key criteria for each impairment stage, the corresponding expected credit loss methodology, and the basis for interest revenue recognition as described by Bank for International Settlements (2017). It serves as a structured reference for understanding the differences in credit risk treatment and provisioning requirements across the three-stage framework introduced by IFRS 9.

Table 1. Three-Stage Credit Impairment Classification.

Stage	**Criteria**	**ECL Calculation**	**Interest Revenue**
Stage 1	Newly originated or performing loans with no SICR.	12-month ECL: Expected credit losses from default events possible within the next 12 months.	Recognised based on the gross carrying amount.
Stage 2	Loans with a SICR since initial recognition but not credit impaired.	Lifetime ECL: Expected credit losses from all possible default events over the remaining life of the asset.	Recognised based on the gross carrying amount.
Stage 3	Loans that are credit impaired (e.g., defaulted or with objective evidence of impairment).	Lifetime ECL: Reflects losses expected from a default that has already occurred. Typically includes judgmental overlays.	Recognised based on the net carrying amount (i.e., after deducting the ECL).

Despite the fewest loans are allocated to stage 3, majority of European banks' impairment provisions are allocated to stage 3 loans (on average 72 % - 81 % during 2019 - 2020) (European Banking Authority, 2021, p. 33–34). The allocation for stage 2 loans has representatively been around 12 % - 19 % and for stage 1 loans 8 % - 10 %.

2.3 Theoretical Foundations of IFRS 9

Following the financial crisis of 2007-09, backward-looking provisioning methods of the time, were accused of resulting in ”too little, too late” provisioning (Behn & Cyril, 2023, p. 4–9). The methods used at the time relied primarily on IL approaches (such as IAS 39 Financial Instruments: Recognition and Measurement IAS 39), which required banks to book provisions only after apparent evidence of credit loss (Behn & Cyril, 2023, p. 4–9).

The impact loan loss provisioning on bank stability had however been debated already before the crisis. In one of the most important studies of the time on loan loss provisioning, Laeven and Majnoni (2003) found empirical evidence on delayed recognition of credit losses, procyclical provisioning behaviour and income smoothing (discussed later in Section 3). Additionally, they highlighted that the provisioning behaviour is differentiated across the banks due to very different regulatory and institutional frameworks. As a result, they argue that loan loss provisioning should form a fundamental part of bank capital regulation. Today, although the European Central Bank (ECB) is not an accounting supervisor, it holds a prudential mandate that allows it to challenge and influence banks’ provisioning practices when concerns arise regarding the adequacy of risk coverage (European Central Bank, 2024b, pp. 2).

The procyclical behaviour of provisioning practices during financial crisis, is evident in Figure 1. The figure presents the evolution of weighted average provisioning ratios (loan loss provisions over total gross loans) over time (Behn & Cyril, 2023, p. 38).

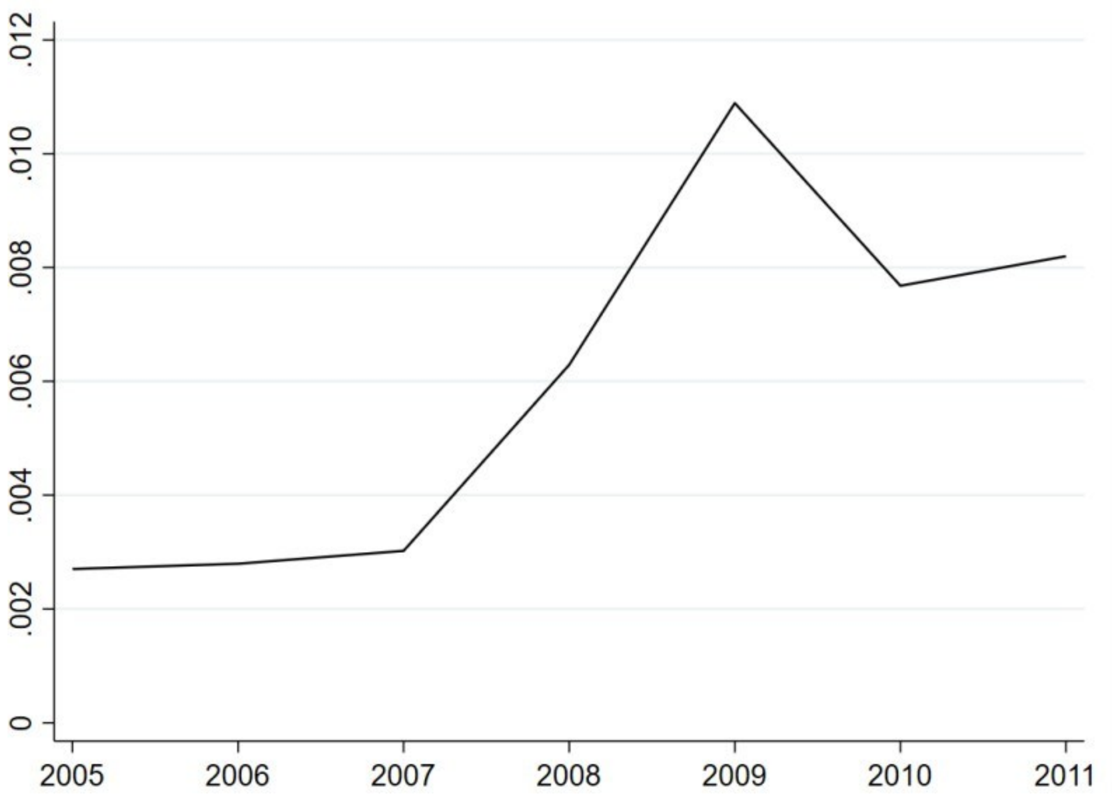

Figure 1. Evolution of loan loss provisioning ratios during the global financial crisis (Behn & Cyril, 2023, p. 38, Fig. 1).

Following the widespread criticism of the provisioning behaviour during time, and after the provisioning ratios quadrupled during the crisis, The Financial Stability Forum (FSF) (predecessor to today's Financial Stability Board (FSB)) urged accounting standard setters to re-evaluate the IL approaches, to adopt more forward-looking approaches Behn and Cyril (2023, p. 4). Consequently, the IFRS 9 Expected Credit Loss (ECL) approach was developed and later enforced in 2018.

As described in Section 2.2, the IFRS 9 approach necessitates that banks incorporate past events, current conditions, and forward-looking information in calculation of ECL. Prior to implementation of IFRS 9, forward-looking provisioning methods were anticipated to mitigate procyclicality and improve the timeliness of loss recognition (Novotny-Farkas et al., 2024, p. 2). Consequently, the aim of the IFRS 9 ECL approach is timelier loss recognition, based on estimated future credit losses (Behn & Cyril, 2023, p. 4). The estimations are usually obtained from statistical models dedicated for this purpose and owned by the banks. Additionally, banks may apply overlays based on expert judgment as is to be discussed in Section 2.4.

According to Ozdemir (2021), beyond its technical changes, IFRS 9 represents a broader shift in financial reporting, placing risk assessment at the core of impairment recognition. This transition aligns financial disclosures with risk management practices, as IFRS 9 replaces the traditional accounting-based impairment model with a risk-based approach. Provisions are now estimated using statistical measures, macroeconomic forecasting and scenario analysis, overseen by the risk function. This integration reinforces the Risk function's role in financial institutions, requiring ongoing assessment of ECL.

Despite its strong theoretical foundation and broad support, IFRS 9 was also critically examined prior to its implementation. During the interim period between the introduction of IFRS 9 and its implementation, Novotny-Farkas (2016) assessed its anticipated effects on financial stability and provisioning practices. The paper identified raised concerns about managerial discretion. A potentially major issue highlighted in the paper was that the stepwise recognition of loan losses driven by SICR identification (see Table 1), could lead to over- or understatement of provisions, depending on how SICR was assessed in practice. Moreover, the paper suggests that untimely SICR identification under IFRS 9 could result in significantly increased provision volatility.

2.4 IFRS 9 Provisioning Practices

Although IFRS 9 requires banks to incorporate all reasonable information about past events, current conditions, and forward-looking factors (Bank for International Settlements, 2017, p. 1–2), it does not mandate the use of statistical models for estimating ECL (European Central Bank, 2024a, p. 4). As a result, banks employ a combination of statistical models and management overlays[2] to estimate ECL and determine provisioning levels (European Central Bank, 2024a, p. 3).

A recent European Central Bank (2024a) review exercise on provisioning practices indicates that approximately three-quarters of provisions in banks' performing loan portfolios are generated by statistical models, with overlays accounting for the remaining share. Accordingly, statistical models represent the primary tool for calculating impairment provisions. Further, the European Central Bank (2024a) notes that when sufficient data are lacking, banks should rely on overlays rather than attempt to model novel risks without appropriate data. Additionally, they emphasize that both approaches require the use of sound and robust methodologies.

According to Gubareva (2021), despite the widespread adoption of IFRS standards, the principles-based IFRS 9 does not prescribe specific methodologies for estimating ECL. Moreover, she claims that the flexibility has led to variation in ECL calculation methods across the industry, and a common consensus on best practices is missing. Such variation in estimation approaches may result in inconsistencies in the accuracy of ECL estimates across banks, potentially undermining the effectiveness of the ECL framework at the industry level. In contrast, Beerbaum (2024) finds in his qualitative analysis that, despite the fundamental shift in accounting principles introduced by IFRS 9, many banks adopted an adaptive transition strategy. Rather than developing entirely new models, they modified existing regulatory capital risk models to comply with IFRS 9 requirements. This alignment with regulatory capital models may arguably serve as a starting point for cross-industry consistency and consensus.

Beerbaum (2024) explains that ECL models can be categorized into direct and indirect approaches. Direct methods estimate ECL by using its underlying drivers as explanatory

[2] As IFRS 9 does not define overlays, various terms are used to describe this practice, including management adjustments, post-model adjustments, and top-level adjustments (European Central Bank, 2024a, p. 4).

variables, whereas indirect methods rely on modularization or simulation to derive expected losses. Typically, direct approaches align with Cash Flow based Model (CFM) models, while indirect approaches are characteristic of Exposure based Model (EBM) models. According to Beerbaum (2024), most large EU banks use EBM models based on the Basel framework to estimate ECL. These models incorporate Exposure at Default (EAD), PD, and Loss Given Default (LGD) as key components. As described and given by Schutte et al. (2020, p. 3–5, Eq. 1), a general simplified formulation of such an indirect EBM ECL model can be expressed as follows:

$$ECL_i = PD_i \times LGD_i \times EAD_i, \tag{1}$$

where:

- PD_i, LGD_i, and EAD_i is the PD, LGD, and EAD of account *i* over the total time horizon, $t \in [0, \ldots, T]$.
- The time horizon t is given by t ∈ [0, . . . , T].
- T is determined by the stage (12 months for Stage 1 and lifetime for Stage 2 & 3).

As briefly touched upon, the type of model presented by Schutte et al. (2020, p. 3–5, Eq. 1) predates the implementation of IFRS 9 and was primarily used in regulatory capital and collective provisioning frameworks (2024, pp. 6–7). As Beerbaum (2024) explains, these models required modifications to comply with IFRS 9 principles, particularly through the incorporation of forward-looking macroeconomic forecasts, point-in-time (PiT) estimates, and the removal of embedded conservatism. Empirical evidence by Beerbaum (2024) indicates that many banks adapted these existing models rather than fully transited to cash flow-based impairment approach.

According to the provisioning review exercise by European Central Bank (2024a), most banks use overlays, which the ECB considers appropriate provided they are based on sound and robust methodology. In the exercise, overlays are defined as adjustments made after the statistical model has been operated. However, banks can also introduce adjustments within the statistical model itself, including changes to model inputs, parameters or calibration. According to the European Banking Authority (2023), overlays remain the most common adjustment method. Importantly, European Central Bank (2024a) note that applying overlays at the total ECL level, although still widespread, should be avoided. The authors argue that such practices conflict with the principles of IFRS 9, which require banks to incorporate all identified risks into the Probability of Default (PD), thereby ensuring that these risks are appropriately reflected in staging through the assessment of SICR.

The review exercise by European Central Bank (2024a) finds that most banks apply overlays due to insufficient data for sound and robust modelling. In such cases, the European Central Bank considers overlays the most appropriate solution, noting that the worst alternative would be to ignore these emerging risks entirely. However, the review also points out that a key drawback of overlays is that those can rely on subjective judgment. If best practices are not followed, it can become difficult to distinguish which risks the overlays are intended to address, thereby reducing transparency and comparability. Finally, the review also highlights that banks may use overlays opportunistically, for example, to support earnings management objectives.

3 Literature Review and Theoretical Foundations of the Research Questions

This section reviews the theoretical foundations and empirical literature relevant to the study, focusing on four key concepts: earnings management (related to RQ1), capital management (RQ2), delayed loss recognition (RQ3), and procyclicality in bank provisioning practices (RQ4). The chapters outline how these mechanisms have been conceptualized and investigated in prior research, with particular attention to the transition from incurred loss to expected credit loss frameworks under IFRS 9. By synthesizing these insights, the section establishes the foundation for the empirical analyses presented later in the study.

3.1 Earnings Management

The earnings smoothing hypothesis posits that banks reduce impairments when earnings are expected to be low and increase them when earnings are high, relative to other fiscal periods (Bouvatier & Lepetit, 2008, p. 517)[3]. Bhat (1996) argues that income smoothing stems from the pursuit of stable earnings, which, together with consistent earnings growth, is often seen as a key characteristic of a pristine bank. According to Bhat, banks may engage in income smoothing for several reasons. It enhances their perceived stability among investors, regulators and legislators. It also supports steady compensation and dividend policies. Additionally, it may reduce the tax liabilities and finally, it can strengthen the reputation of management and promote stock price stability for publicly listed banks. Additionally, Laeven and Majnoni (2003, p. 182) note that although earnings smoothing is often viewed critically by accounting professionals, it can help mitigate procyclicality and lower the risk that a bank will need to cover losses with its capital.

[3] In academia both terms ”earnings smoothing” and ”income smoothing” are used for describing this phenomenon. For clarity, this study will opt for the prior, as it is better aligned with later naming convention of variables used in this study.

The accounting literature, by contrast, emphasizes that earning smoothing introduces judgmental elements and limits the comparability of financial results between companies. As a result, income smoothing is seen more favourably in economic research compared to the accounting field.

The earnings smoothing hypothesis is well established in literature and has been studied for decades. However, there is also criticism. For example, Beatty and Liao (2014, p. 378) argue that the theoretical foundation is limited, lacking the objective of earnings smoothing and overlooking depositor information problems.

Literature review by Beatty and Liao (2014) shows that academic research on earnings smoothing has typically presumed that motives for earnings smoothing depend on earnings before impairments, as that is the most significant bank accrual and thereby has a material impact on banks' earnings. According to (Laeven & Majnoni, 2003, p. 182), banks can smooth their earnings by increasing provisions when actual credit losses are lower than ECL (contributing to loan loss reserves), and by drawing from the reserves when the actual losses are higher than expected. According to European Central Bank (2024a, p. 6– 7) under the IFRS 9 regime, earnings smoothing is often done via overlays that contribute to the final provisions. Additionally, Novotny-Farkas (2016, pp. 213) notes the managerial discretion over determination of SICR under IFRS 9 can too be used as a means for smoothing earnings.

Figure 2 illustrates the earnings smoothing mechanism. During economic expansions, banks experience low actual loan losses and can increase provisions to build reserves with the cost or aim of lower reported earnings. In contrast, during recessions, when actual loan losses rise, banks may utilize these reserves to cover credit losses, resulting in more stable earnings despite the downturn.

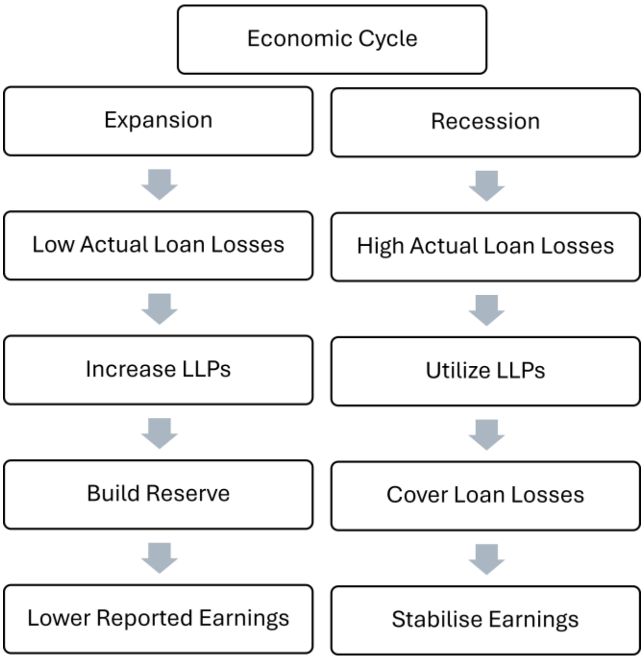

Figure 2. Earnings Smoothing Mechanism During Expansion and Recessions.

The earnings' smoothing hypothesis has been extensively studied, but the empirical results have remained mixed (Laeven & Majnoni, 2003, p. 183); (Beatty & Liao, 2014, p. 361). Notably, after noting this inconsistency, Laeven and Majnoni (2003) themselves provide evidence of earnings smoothing, documenting a positive relationship between earnings before loan loss provisioning and loan loss provisions, using cross-country data from 1988–1999. Beatty and Liao (2014) instead propose in their more recent study that the results seem to be sensitive to methodological choices. As both studies are from the time before IFRS 9, those discuss only provisioning practices under the IL regime.

European Central Bank (2024a, p. 6–7) confirm that the positive correlation between earnings before impairments and impairments has persisted under the ECL approach. Recent academic research by Novotny-Farkas et al. (2024) similarly finds a positive and statistically as well as economically significant relationship between earnings before impairments and impairments. Although fewer studies have examined the earnings smoothing hypothesis under the ECL framework, early evidence suggests that the practice persists under IFRS 9. As discussed at the beginning of this chapter, whether earnings smoothing is regarded as a desirable countercyclical mechanism or a problematic, judgmental practice undermining the comparability of financial results across banks depends on whether it is viewed from an economics or accounting perspective.

To summarize, the earnings smoothing hypothesis suggests that banks adjust impairments over time to achieve more stable earnings, reducing provisions when earnings are low and increasing them when earnings are strong. Motivation for smoothing includes enhancing stability in the eyes of investors, regulators, and the public, supporting compensation and dividend policies. While the hypothesis is well-established in literature, empirical evidence has been mixed, in part due to differences in methodological approaches. Although most research has focused on the incurred loss regime, early evidence suggests that earnings smoothing continues under the forward-looking ECL framework of IFRS 9. The practice remains viewed more favorably in economics than in accounting, where concerns about discretion and reduced comparability persist. Notably, while the practice is sometimes viewed critically for reducing transparency and comparability, it may also have the positive effect of mitigating procyclicality in bank lending.

3.2 Capital Management

The capital management hypothesis posits that those banks with weaker capital levels provision less than better-capitalized banks (e.g., Novotny-Farkas et al., 2024, p. 22; Behn & Cyril, 2023, p. 2). Behn and Cyril (2023) describe this as a strategy of "provisioning as much as you can afford." Because weakly capitalized banks have less capital headroom than better-capitalized competitors, they cannot afford to provision at the same level. As discussed in Section 3.1, it is important to recognize that banks may also have incentives to increase provisioning during expansions to manage earnings. As a result, better-capitalized banks may not only provision more than weakly capitalized banks but also comply with the strategy of provision as much as they can afford, rather than settling for lower provisioning levels.

According to Beatty and Liao (2014), under Basel capital adequacy requirements, banks may have incentives to book low provisions to avoid breaching minimum regulatory capital requirements. Unlike in the pre-Basel period, provisions now reduce the Tier 1 capital ratio, creating a clear incentive for weakly capitalized banks to limit provisions. Beyond merely meeting minimum capital requirements, banks may also under-provision to avoid weakening their capital to a point where they are forced to restrict lending (Behn & Cyril, 2023, p. 2–3).

Behn and Cyril (2023) highlight that capital management can have both positive and negative effects. On the positive side, it may implicitly mitigate procyclicality by helping banks avoid forced lending cuts. On the negative side, such discretion reduces transparency and can lead to an underestimation of credit risk. In the latter case, if and when risks materialize, under-provisioned banks may face more severe challenges, including difficulties related to solvency.

Behn and Cyril (2023) link this capital management behaviour specifically to impaired assets, suggesting that banks may attempt to delay or reduce impairments on such assets. Their empirical analysis supports this view, showing that weakly capitalized banks classify fewer loans into Stage 2 prior to default (delayed recognition of SICR). Additionally, for exposures that remain in Stage 1 until default, provisioning ratios are significantly lower after the default, compared to better-capitalized banks. As discussed earlier in this study, banks may opportunistically use various discretionary measures available under IFRS 9 to achieve these lower provisions.

Behn and Cyril (2023) find that banks with lower capital have significantly lower provisioning ratios compared to better-capitalized competitors. These lower-capitalized banks also classify fewer loans into Stage 2 prior to default. Furthermore, after loans are moved to Stage 2, weakly capitalized banks book lower provisions than better-capitalized banks. Finally, they find evidence that IFRS 9 has strengthened the association between capital position and provisioning ratios, suggesting that capital management plays a more prominent role under the IFRS 9 regime than before. Novotny-Farkas et al. (2024) support these findings, as their regression model identifies a statistically significant negative relationship between Allowances for Credit Losses (ACL) on Stage 2 and a dummy variable distinguishing weakly capitalized banks.

To summarize, the capital management hypothesis suggests that banks with weaker capital positions provision less than better-capitalized banks, reflecting the strategy of provisioning as much as they can afford. Banks may use capital management not only to meet regulatory minimums but also to avoid weakening their capital to a level that would constrain lending. While such behaviour can help dampen procyclicality, it also reduces transparency and may lead to underestimation of credit risk. Empirical evidence under the IFRS 9 framework indicates that capital management plays a significant role in shaping provisioning behaviour, with weakly capitalized banks showing systematically lower provisioning ratios and less timely loan classification.

3.3 Delayed Loss Recognition

Akins, Dou, and Ng (2017, p. 455) describe loan loss recognition as an accrual process for banks to recognize future expected loan losses during the current fiscal period. Consequently, banks build up reserves to capture these expected losses.

Whether loan loss recognition is considered timely or delayed depends on whether banks must absorb losses through their capital or whether the loan loss reserves built through provisioning are sufficient to cover the losses (Laeven & Majnoni, 2003, p. 189); (Beatty & Liao, 2011, pp. 1–3). In practice, delayed provisioning can thus be considered a failure to build enough loan loss reserves in time (through provisioning). According to Behn and Cyril (2023, p. 4), timely provisioning ensures that the banks can endure credit risks if they materialize, without endangering neither their own solvency nor financial system stability.

At the time, Laeven and Majnoni (2003) illustrated this relationship between provisions and capital using a probability density function, shown in Figure 3. As the figure was developed in the context of the IL regime prevalent in 2003, it may not fully capture the forward-looking nature of impairment provisioning under IFRS 9 or the more complex interaction between provisions and regulatory capital in today's framework (Novotny-Farkas, 2016). Nevertheless, it serves as an illustrative tool for understanding the delayed loss recognition.

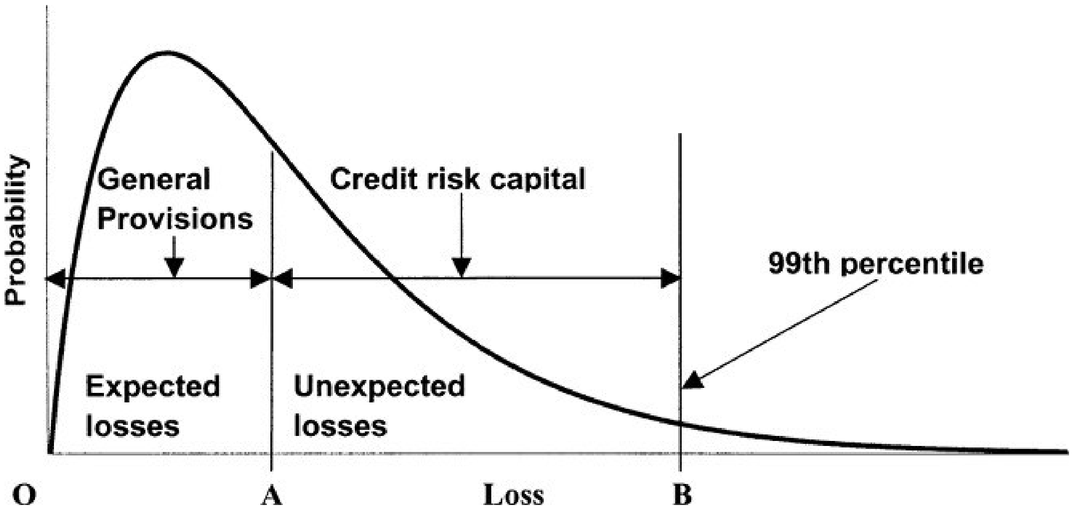

Figure 3. Probability density functions of loan losses, provisions, and economic capital (Laeven & Majnoni, 2003, Fig. 1, p. 196).

Literature suggests three explanations for delayed loss recognition. First, prior to forward looking ECL approaches, accounting rules under IL approach were seen to constrain timely loan loss recognition (Bischof, Laux, & Leuz, 2021, p. 1204). For example, under IAS 39 accounting standard, banks were guided to book provisions only after apparent evidence of credit loss (European Central Bank, 2024b, p. 4–9). Generally Accepted Accounting Principles (GAAP) was even more strict and required losses to be probable and estimable (Bischof et al., 2021, p. 1204). Today under the forward-looking IFRS 9 regime and ECL approach, the explanation is not valid anymore. The two other explanations or incentives that are still relevant are earnings management and capital management (e.g., Bischof et al., 2021, p. 1204; Bikker & Metzemakers, 2005, p. 145). Practically, delayed loss recognition can be seen as means for earnings and capital management and ultimately driven by the motives for those[4].

Under IFRS 9, banks can use various discretionary measures to delay loan loss recognition. Most notably, they can postpone sorting loans into Stage 2 and thereby limit or delay the increased provisioning for lifetime losses on Stage 2 and Stage 3 exposures (Behn & Cyril, 2023, p. 26). Behn and Cyril (2023) argues that the forward-looking nature of the IFRS 9 framework gives banks greater discretion compared to the backward-looking IL approach. This discretion is inherent, as estimates of future expected losses depend heavily on forward-looking assumptions and managerial judgment. Moreover, because the IFRS 9 framework is principles-based, the standards allow for varying interpretations, and banks may apply different modelling approaches and assumptions.

Timeliness of loan loss recognition has been examined in literature using various approaches. Laeven and Majnoni (2003) provide econometric evidence of delayed provisioning by analysing the relationship between loan loss provisions, earnings, loan growth, and GDP growth. Their findings show that banks tend to book higher provisions during periods of negative earnings compared to profitable periods. As banks cannot rely on profits to fund provisions during loss-making fiscal years, this implicitly means they must draw on their capital. As discussed previously, that can be viewed as an indicator of delayed loan loss recognition due to insufficient prior reserves.

In a more recent study conducted under the IFRS 9 regime, Novotny-Farkas et al. (2024) examine delayed loss recognition, specifically including the delayed identification of a SICR. According to Behn and Cyril (2023, p. 10–11), a SICR triggers a transfer to Stage 2 and requires provisioning for expected lifetime losses instead of 12-month expected losses. Delayed identification of SICR therefore effectively results in delayed provisioning, as provisions do not yet reflect the fully expected loss. Leveraging this staging mechanism introduced under IFRS 9, Novotny-Farkas et al. (2024) investigates the relationship

[4] For earnings management motives, see Section 3.1 and for capital management Section 3.2.

between proxies for SICR, as a forward-looking indicator, and nonperforming loans as a backward-looking measure, in relation to allowances for Stage 2 and Stage 3 assets. Their results show that although banks increase provisions in response to early signs of credit risk (such as SICR), provisioning is more strongly associated with backward-looking indicators like nonperforming loans.

A study from Beatty and Liao (2011) shows that delayed loss recognition can amplify the procyclicality of bank lending, creating broader risks for the financial system. This occurs because when loan loss reserves are not sufficient to absorb losses, more provisioning is needed resulting in reduced capital adequacy. In addition, they find that during recessions, banks with more substantial delays are more prone to capital crunches than banks with smaller delays.

Although the introduction of IFRS 9 and its forward-looking ECL framework was intended to reduce delayed loan loss recognition, Novotny-Farkas et al. (2024) find that banks continue to delay the recognition of credit losses. Encouragingly, Lopez-Espinosa and Penalva (2023), in their analysis of Spanish banks, find that IFRS 9 has improved the timeliness of credit loss recognition. However, they caution that due to research design limitations and data constraints, their findings should be interpreted as mostly descriptive and the conclusions only as preliminary evidence.

To summarize, the literature defines loan loss recognition as the process by which banks account for expected credit losses in their financial statements. Banks may delay this recognition to manage earnings or capital, using discretion over loan classification and provisioning levels. The evolution from incurred loss models to the forward-looking IFRS 9 framework was designed to improve the timeliness of recognition by incorporating forward-looking measures. While delayed loss recognition can amplify the procyclicality of bank lending and increase systemic risk, recent empirical studies provide preliminary evidence that IFRS 9 has helped mitigate these delays, although some challenges driven by discretion remain.

3.4 Procyclicality

Procyclicality can be defined as a phenomenon in which banks' lending practices move in tandem with the cycles of real economy (European Central Bank, 2005, p. 56–58). In practice, the phenomenon manifests as increased lending during economic expansions and reduced lending during downturns. Such behaviour implicitly amplifies economic fluctuations, exacerbating recessions and intensifying booms.

According to European Central Bank (2005, p. 56–58), banks' activities in general have pro-cyclical characteristics, which are considered to result from the existence of asymmetric information and market imperfections. Athanasoglou, Daniilidis, and Delis (2014, p. 60–62) explain that asymmetric information arises because borrowers possess more knowledge about their own financial situation and risk profile than lenders. Further, they link this to the issue of adverse selection, positing that under imperfect information, banks are more willing to increase loan granting during expansions, when borrowers are less risky. The authors note that the problem of asymmetric information also affects provisioning, as higher provisions during upturns may be regarded by the market as negative signals about the bank's financial condition (p. 61). However, this is not considered the main driver of provisioning procyclicality, as will be discussed next.

After the global financial crisis, the general consensus emerged that provisioning under IL model of the IAS 39 accounting standard contributed to lending procyclicality (Novotny-Farkas et al., 2024, p. 1). Whether provisioning is pro- or counter-cyclical is seen to depend on whether it follows a backward- or forward-looking approach (Pool, de Haan, & Jacobs, 2015, pp. 124–125). The problem with backward-looking provisioning is that it is applied only after clear evidence of credit loss emerges, meaning that during economic upturns, when there are fewer non-performing loans, provisioning remains low. Conversely, during downturns, when risks materialize and non-performing loans increase, provisioning rises. As Bouvatier and Lepetit (2012, p. 25–26) argue, insufficient provisioning during upturns understates the true cost of lending, which leads banks to ease lending standards. In contrast, during downturns, when loan loss reserves have not been built up, banks are forced to tighten lending.

Over time, various studies have confirmed the pro-cyclical nature of provisioning under IAS 39 by examining the relationship between provisioning, GDP, and loan growth. For example, Laeven and Majnoni (2003) find negative relationships between provisioning and GDP, as well as between provisioning and loan growth, for an international sample of banks during 1988–99. Similarly, Bikker and Metzemakers (2005, p. 148–153) document a negative association between GDP growth and loan loss provisioning using data from 29 Organisation for Economic Co-operation and Development (OECD) countries during 1991–2001, while Bouvatier and Lepetit (2008, p. 518–520) report comparable results for European commercial and cooperative banks from 1992–2004. As discussed in Section 2.3, later the evidence of procyclicality triggered the FSB to initiate a more forward-looking replacement for the IL model in an attempt to mitigate lending procyclicality caused by backward-looking provisioning practices. At the time, theoretical literature posited that forward-looking impairment provisioning methods could mitigate procyclicality, reduce economic volatility, and enhance the effectiveness of monetary policy, in contrast to backward-looking approaches (Pool et al., 2015, pp. 124-125). Procyclicality would be mitigated by building up provisions already during good times, thereby creating a reserve that absorbs the impact of losses when conditions deteriorate. This forward-looking approach would help smooth the cost of lending across the cycle and reduce the need for abrupt adjustments in credit supply during downturns.

Although the ECL model was expected to mitigate procyclicality of provisioning, recent studies suggest that the pro-cyclical pattern persists. Novotny-Farkas et al. (2024), using data on European banks from 2018–2022, find a negative relationship between GDP and impairments, despite focusing exclusively on banks reporting under IFRS 9. In addition, they find that provisioning reduced lending during COVID-19[5], distinguishing the former as accounting procyclicality and the latter as lending procyclicality (p. 18).

Interestingly, Athanasoglou et al. (2014, p. 63–64) suggest that certain market imperfections can partially mitigate procyclicality, for example through earnings smoothing, where management's desire to stabilize reported earnings leads to countercyclical provisioning behaviour (see also Section 3.1).

To summarise, theoretical literature emphasizes that the procyclicality of provisioning arises largely from backward-looking practices, which amplify credit cycles by lowering provisions during expansions and increasing them during downturns. Forward-looking approaches, such as those introduced under the ECL model, were designed to address this issue by encouraging the gradual accumulation of reserves during good times. However, recent evidence suggests that, despite these theoretical advances, procyclical dynamics persist in practice, making the study of both accounting and lending procyclicality highly relevant.

[5] The relationship between impairments and lending was positive over the full sample period.

4 Empirical Analysis

The aim of this study is to examine the determinants of impairment provisioning under IFRS 9. The empirical analysis is inspired by the working paper by Novotny-Farkas et al. (2024), which, although not yet peer-reviewed, presents the most comprehensive publicly documented model for analysing impairment provisioning determinants. While prior literature typically applies frameworks developed for incurred loss models, their approach adapts the regression design to reflect the forward-looking and stage-based features of IFRS 9 (Novotny-Farkas et al., 2024, p. 13–14). Despite its working paper status, the study is authored by researchers with strong academic backgrounds and prior publications related to IFRS 9.

In their study, Novotny-Farkas et al. (2024) develop an empirical OLS model to explain impairment provisions under IFRS 9, incorporating stage-specific credit risk measures, portfolio composition, macroeconomic variables, and indicators of managerial discretion. Their approach captures both economic and discretionary drivers of provisioning, while accounting for the key structural features of the ECL framework. This study adopts the same methodological approach with minor adjustments. Specifically, all data not publicly available are replaced with freely accessible public data sources, and the analysis period is extended.

While Novotny-Farkas et al. (2024) examine the period from 2018:Q4 to 2022:Q2, this study expands the sample until 2024:Q2, allowing for a more robust and comprehensive assessment that incorporates the post-pandemic macro-financial environment. This extension results in a sample that is approximately 53 percent longer in terms of quarterly cross-sections. Importantly, the analysis in this study focuses solely on the impairment provisioning determinants analyses and does not adopt the authors' other models nor analyses. Moreover, this analysis does not differentiate between COVID-19 and non-COVID-19 periods.

4.1 Data

The primary source of data for this study is the European Banking Authority's (2024a) EU-wide Transparency Exercise, which is also employed in the study by Novotny-Farkas et al. (2024). The exercise is conducted twice a year, with each round adding to the cumulative dataset over time. These publicly available datasets provide detailed quarterly disclosures at the individual bank level, including information on exposures, capital ratios, and credit risk indicators. The use of the same dataset ensures comparability with previous findings and enables a meaningful assessment of their robustness over an extended period.

In addition to the Transparency Exercise (European Banking Authority, 2024a), a number of macroeconomic and sentiment related variables are included from various sources. Country-level GDP growth rates are retrieved from Eurostat (2024), while forward-looking macroeconomic expectations—specifically the four-quarter-ahead GDP growth forecasts—are obtained from the European Central Bank's Survey of Professional Forecasters (ECB SPF) (European Central Bank, 2024c). Country-level economic and political uncertainty is captured using the World Uncertainty Index (WUI), a quarterly measure based on text analysis of Economist Intelligence Unit country reports by Ahir, Bloom, and Furceri (2018). These external sources are all publicly accessible and contribute essential context to understanding the macroeconomic environment faced by individual banks.

All data used in this study is freely available, and particular care has been taken to document the methodology used to transform raw figures into regression-ready variables. This approach aligns with the principles of transparency and reproducibility and serves as a reference point for future research utilizing similar sources.

4.1.1 Sample Scope and Period

The sample is based on data from the European Banking Authority's Transparency Exercise (2024a). It includes only banks that report FINREP data at the consolidated level on a quarterly basis and report financial statements in accordance with IFRS accounting standards. The final sample consists of 127 unique banks across 27 European countries, yielding a total of 2,266 bank-quarter observations.

As illustrated in Figure 4, the distribution of banks across countries is heterogeneous. The largest representations come from Germany (15 banks), Italy (13), Spain (13), and France (11), reflecting the relative size of their banking systems. The Nordic region is also well represented, with a total of 19 banks from Sweden (5), Denmark (4), Finland (4), Norway (3), and Iceland (3). The Eastern-European and Balkan countries are less well represented.

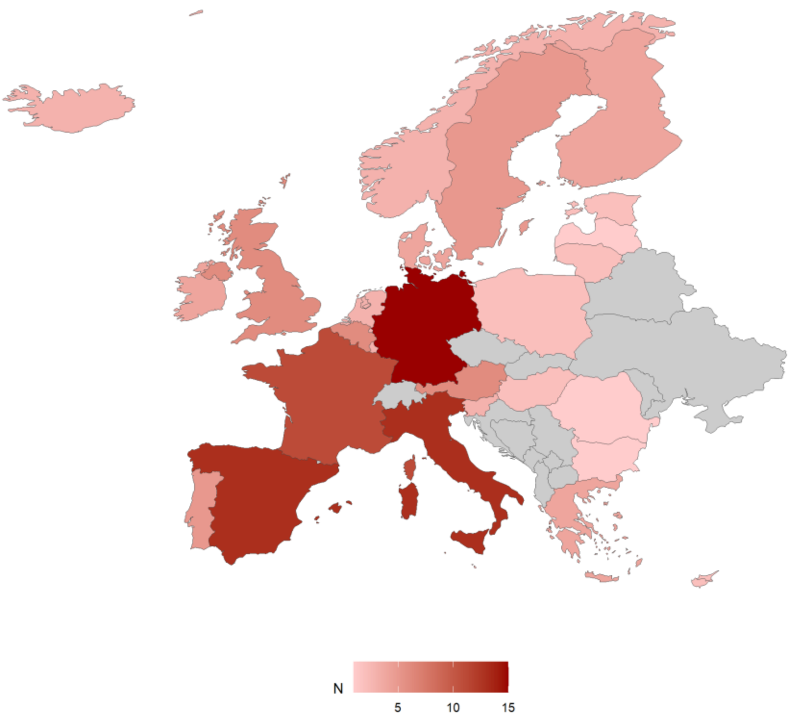

Figure 4. Number of Banks by Country in the Sample.

The sample includes both Euro area and non-Euro area countries, providing a balanced regional scope. Out of the 27 countries, 19 are members of the Euro area, representing over 75% of all banks. While the analysis does not focus on comparisons between currency regimes, the inclusion of countries outside the Eurozone (such as the United Kingdom, Sweden, and Denmark) adds contextual diversity in terms of regulatory and monetary environments.

The sample period extends from 2018:Q4 to 2024:Q2, encompassing a total of 23 quarters. This represents a significant extension compared to the study by Novotny-Farkas et al. (2024), which covers the period from 2018:Q4 to 2022:Q2 and forms the basis for the loan loss determinants model adopted in this thesis. By adding eight additional quarters, corresponding to an increase of approximately 53%, this study enables a broader analysis over a longer and more recent time span.

Extending the sample beyond the timeframe used by Novotny-Farkas et al. (2024) enhances the robustness of the analysis by incorporating additional quarters. In addition to the increased time span, the extended sample captures a macroeconomic environment that differs markedly from the earlier period. This allows for a more comprehensive assessment of banks’ behaviour across varying economic conditions.

Figure 5 depicts the average CBC (average of the OECD Composite Consumer Confidence and Business Confidence indexes) and GDP Growth Over Time. Both indicators are calculated as averages of variable values in the sample, variables being defined as presented in Section 4.2.6 The grey-shaded region marks the sample period used by Novotny-Farkas et al. (2024), providing a point of comparison with the extended timeframe examined in this study.

Following the period definitions in Novotny-Farkas et al. (2024), the years 2018:Q4 to 2019:Q4 and 2021:Q1 to 2022:Q2 are considered non-COVID periods, while 2020:Q1 to 2020:Q4 represents the COVID period. Based on GDP growth, the COVID period is marked by substantial volatility in economic activity, with a sharp contraction in 2020Q2 followed by an equally pronounced rebound in 2020Q3. These movements reflect the shock and recovery associated with the pandemic.

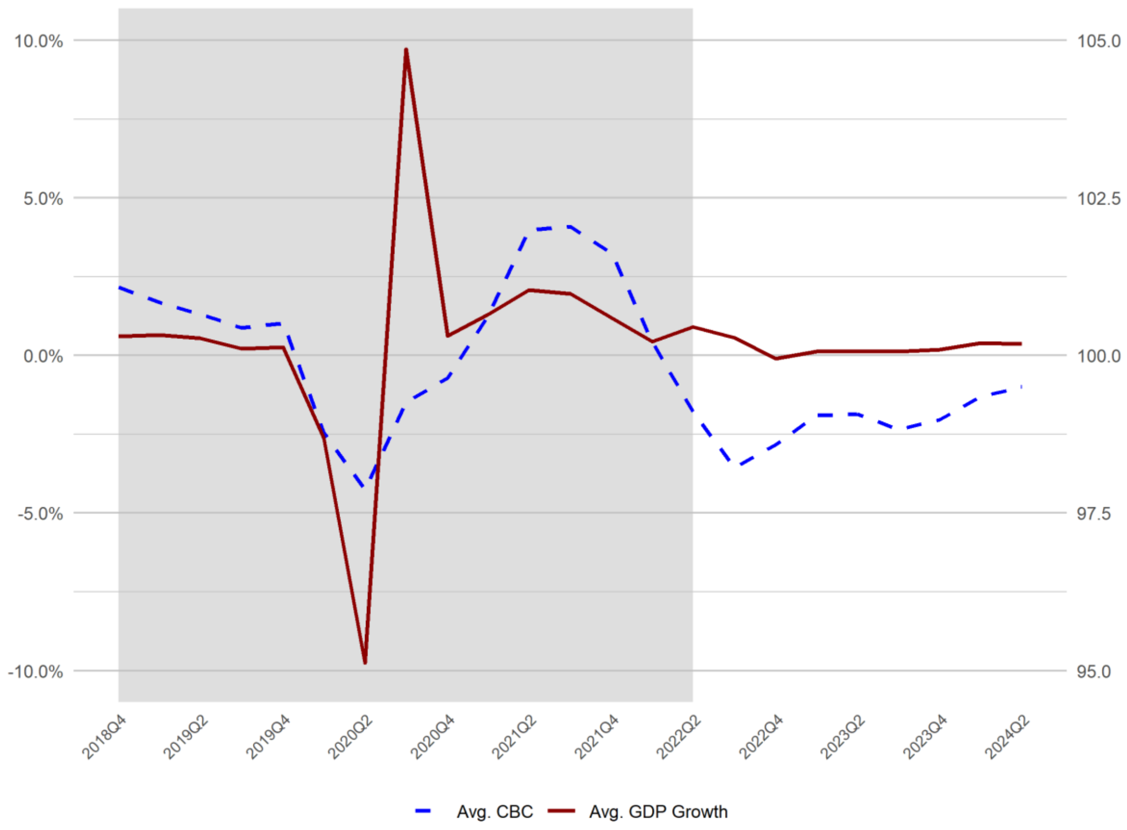

Figure 5. Average CBC and GDP Growth Over Time.

Importantly, the extended post-2022 period examined in this study differs not only from the COVID period but also from the non-COVID phase as defined in Novotny-Farkas et al.'s study (2024). While their non-COVID periods include both pre-pandemic normalcy and the recovery phase of 2021–2022, the prolonged period in this study reflects a new macroeconomic environment characterized by relative stability and muted GDP growth fluctuations around zero, and a phase of sharply rising interest rates. This distinct back-drop enhances the relevance of the extended timeframe, allowing for an analysis of banks' behaviour in a qualitatively different phase of the economic cycle.

Similarly, the Composite Business and Consumer Confidence (CBC) indicator mirrors this evolution. During the COVID period, CBC levels dropped sharply before rebounding strongly. In the extended period, however, CBC values steadily declined from early 2022 onward and later stabilized at subdued levels.

Crucially, the extended period examined in this study captures a significantly different economic and financial context compared to the timeframe analysed by Novotny-Farkas et al. (2024). While their sample reflects an environment of historically low and negative interest rates, the prolonged period used in this thesis includes the post-2022 phase marked by a sharp and sustained increase in interest rates. As illustrated in Figure 6, the three-month Euribor remained negative throughout the earlier study period and only turned positive afterward, followed by a substantial rise. This development enables an analysis of banks' impairment provisioning under tighter monetary conditions, offering a more complete view of bank behaviour across different phases of the economic cycle.

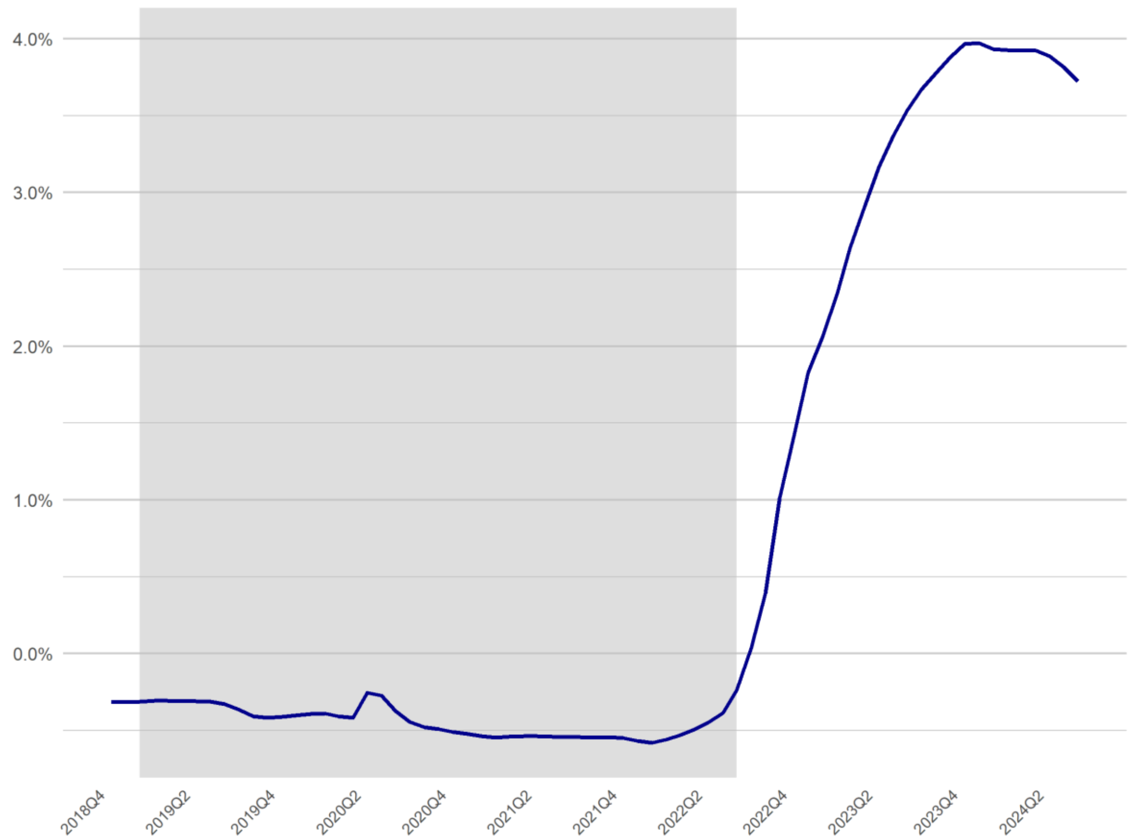

Figure 6. Three-month Euribor Rate in the Euro Area (2018:Q4 - 2024:Q2) (European Central Bank, 2024a).

Overall, the extended sample period adopted in this study offers a substantial improvement over the period used by Novotny-Farkas et al. (2024). By covering both the COVID-19 crisis and the post-crisis adjustment phase, the expanded timeframe enhances the empirical robustness of the analysis. More importantly, it captures a qualitatively different macroeconomic context, moving from a period of extreme volatility and negative interest rates to one characterized by relative stability and tightening monetary policy. This broader scope enables a more comprehensive evaluation of how banks adjust their provisioning behaviour in response to changing economic and financial conditions, ultimately improving the generalizability and relevance of the findings.

4.1.2 Sample Construction and Variable Treatment

The sample is constructed by excluding all observations that do not meet the scope criteria, namely banks that report FINREP data at the consolidated level on a quarterly basis and prepare their financial statements in accordance with IFRS accounting standards. In addition, certain smaller banks included in the EBA Transparency Exercise (European Banking Authority, 2024a) are only available as aggregated entities in the dataset and are therefore excluded from the analysis. After applying these filters, listwise deletion is performed to remove all bank-quarter observations with missing values in any of the variables used in the empirical analysis.

While the final sample covers the period from 2018:Q4 to 2024:Q2, data collection begins in 2018:Q3. This initial cross-section is excluded from the analysis due to data availability constraints, as several variables used in the model require lagged values. Consequently, many observations for 2018:Q3 are incomplete. Nonetheless, this period remains essential for constructing the first valid cross-section in 2018:Q4, where required lagged variables are available.

Although the 2018:Q3 cross-section is used during data preparation to construct lagged values, both the first (2018:Q4) and last (2024:Q2) cross-sections require special handling due to the unavailability of required lag or lead values. Specifically, several time-dynamic explanatory variables, namely the scaled changes in past-due exposures (ΔExp30Days), forborne exposures (ΔExpForb), non-performing exposures (ΔNPE), and expected credit losses (ΔECL) rely on multi-period differencing and lagged asset values for normalization. In 2018:Q4, fallback logic substitutes the unavailable lagged change terms (e.g., $\Delta Exp30Days_{t-1}$) with changes of the current period (e.g., ΔExp30Dayst), and uses $TotalAssets_{t-1}$ in place of TotalAssetst−2 when necessary. Conversely, in the final cross-section (2024:Q2), lead values (e.g., ΔECL_{t+1}) cannot be computed, and are instead replaced by current-period changes (e.g., ΔECL_{t}) normalized using contemporaneous total assets $TotalAssets_{t}$. These adjustments affect the variables ΔECL_{t+1}, $\Delta Exp30Days_{t+1}$, $\Delta ExpForb_{t+1}$, and ΔNPE_{t+1} at the end of the sample, and their respective lagged counterparts $\Delta Exp30Days_{t-1}$, $\Delta ExpForb_{t-1}$, and ΔNPE_{t-1} at the start. This treatment ensures the full-time span of the sample is preserved without compromising the internal consistency of the constructed variables.

4.2 Variables

The variable framework established by Novotny-Farkas et al. (2024) has been adopted to ensure consistency and comparability with prior research. However, due to limited availability of certain proprietary datasets used in their original analysis, alternative proxies for specific variables have been constructed. These alternative variables rely on publicly accessible data sources and are designed to closely approximate the underlying phenomena captured by the original variables.

Next, each category of variables included in the empirical model is discussed separately in the subsections that follow. As a foundation for this discussion, Table 2 and Table 3 present a comprehensive overview of all variables used in the analysis, including their precise definitions, methods of construction, and regression notations.

Table 2 reproduces the variable definitions and constructions from Novotny-Farkas et al. (2024, p. 62-65) reflecting a setup for these variables that is identical to that used in their study. All content in Table 4 is directly drawn from their study, with the exception of the third column, labelled C, which has been added in this study to indicate the corresponding regression coefficient in the primary specification.

Table 3 presents the variables that differ either by data source or definition. The tables explicitly link each variable to its corresponding data source and clearly outline its analytical role, thereby promoting transparency and facilitating replication. Additionally, the column labelled C indicates again the regression coefficient associated with each variable, providing direct reference to their inclusion within the primary regression framework (see Equation 2 in Section 4.2.7).

Table 2. Variable Descriptions: Common Variables (Novotny-Farkas et al., 2024, p. 62-65).

Variable	Description	C
$\%Imp_t$	The variable is equal to the quarterly impairment provision on financial assets not measured at fair value through profit or loss scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise	Y
$\%\Delta ACLS1_t$	The variable is equal to the quarterly change in the allowance for credit losses of stage 1 financial assets (debt securities and loans and advances) measured at amortized cost or at fair value through other comprehensive income scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise	Y
$\%\Delta ACLS2_t$	The variable is equal to the quarterly change in the allowance for credit losses of stage 2 financial assets (debt securities and loans and advances) measured at amortized cost or at fair value through other comprehensive income scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise	Y
$\%\Delta ACLS3_t$	The variable is equal to the quarterly change in the allowance for credit losses of stage 3 financial assets (debt securities and loans and advances) measured at amortized cost or at fair value through other comprehensive income scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise	Y
$\%EBImp_t$	The variable is equal to the quarterly net income before taxes from continuing operations and impairment provisions on financial assets scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise.	β
LOW $CET1_{t-1}$	The variable is equal to an indicator variable that takes the value of one for banks in the lowest quartile of the $CET1_{t-1}$[6] variable in a given quarter and zero otherwise. Data source: EBA's transparency exercise	γ
$CRWA_{t-1}$	The variable is equal to the beginning-of-quarter bank's total credit risk-weighted assets divided by the beginning-of-quarter total assets. Data source: EBA's transparency exercise.	δ
$\%\Delta ECL$	The variable is equal to the quarterly change in estimated weighted-average expected credit losses (proxied by the median LGD and PD experienced by IRB banks on retail and corporate non-defaulted exposures—KRI data retrieved from the EBA risk dashboard) based on the country of a bank's counterparty exposures multiplied by the sum of a bank's exposure at default (net of defaulted exposures), scaled by the beginning-of-quarter total assets in %. In the following three scenarios,	δ

[6] The variable is equal to the beginning-of-quarter bank's CET1 capital (fully loaded) before the allowance for credit losses divided by the beginning-of-quarter total risk weighted assets. Data source: EBA's transparency exercise (Novotny-Farkas et al., 2024).

Variable	Description	C
	we cannot match country-level KRI and Transparency Exercise (TE) data (on average 23.3% (7.4%, median) of banks' corporate and retail exposures). First, KRI data are not available for all countries. If KRI data are not available for a country-level bank exposure outside Europe, we use the average PD and LGD across all available countries for a given quarter. For European exposures without KRI data (Iceland), we use the average PD and LGD across all European countries for a given quarter. Second, the TE provides information for the 10 largest country-exposures at the bank level by exposure types. If the bank has exposures in more than 10 countries, we use the average PD and LGD across all available countries for a given quarter. Third, the TE does not provide exposures at the country-level for 25 smaller banks. We thus use 63 the average PD and LGD from their home country. We caveat that this measure of ECLs is not perfect but uses the best available public information in our context. Data source: EBA's transparency exercise and EBA's risk dashboard	
$\Delta \text{FinAssets}_t$	The variable is equal to the quarterly change in financial assets (the sum of the gross carrying amount of debt securities, loans and advances) at fair value through other comprehensive income and amortized cost classified in stage 1, stage 2 and stage 3 scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	ϑ
FinAssets_{t-1}	The variable is equal to the beginning-of-quarter financial assets (the sum of the gross carrying amount of debt securities, loans and advances) at fair value through other comprehensive income and amortized cost classified in stage 1, stage 2 and stage 3 scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	ϑ
$\Delta \text{Exp30Days}_t$	The variable is equal to the quarterly change in exposures (debt securities, loans and advances: gross carrying amount of debt instruments other than held for trading) that are performing but past due between 30 days and 90 days scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise.	ϑ
$\Delta \text{ExpForb}_t$	The variable is equal to the quarterly change in performing exposures (debt securities, loans and advances: gross carrying amount of debt instruments other than held for trading) with forbearance measures scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise %.	ϑ
ΔNPE_t	The variable is equal to the quarterly change in non-performing exposures (debt securities, loans and advances: gross carrying amount of debt instruments other than held for trading) scaled by the beginning-of-quarter total assets in %. Data source: EBA's transparency exercise	ϑ
Collateralized_t	The variable is equal to the sum of collaterals and financial guarantees received on nonperforming exposures scaled by the beginning-of-quarter non-performing exposures (debt securities, loans and advances: gross carrying amount of debt instruments other than held for trading). Data source: EBA's transparency exercise	μ

Variable	Description	C
InstExp_t	The variable is equal to the beginning-of-quarter institutional original exposures (pre credit conversion factors or credit risk mitigation techniques) scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	μ
CorpExp_t	The variable is equal to the beginning-of-quarter corporate exposures (excluding exposures to small and medium-sized enterprises (SMEs) and measured pre credit conversion factors or credit risk mitigation techniques) scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	μ
RetExp_t	The variable is equal to the beginning-of-quarter retail exposures (excluding exposures to SMEs and measured pre credit conversion factors or credit risk mitigation techniques) scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	μ
SMEExp_t	The variable is equal to the beginning-of-quarter SME exposures (pre credit conversion factors or credit risk mitigation techniques) scaled by the beginning-of-quarter total assets. Data source: EBA's transparency exercise	μ
GDPForGrowth	The variable is equal to the average GDP growth forecast over the next 4 quarters (from quarter t+1 to t+4). Data source: European Central Bank	τ

Table 3. Variable Descriptions: Differentiated Variables.

Variable	Description	C
Size_{t-1}	The size variable is calculated as the natural logarithm of beginning-of-quarter total assets. Unlike Novotny-Farkas et al. (2024), who inferred missing 2018:Q4 total assets using the EAD-to-total-assets ratio, this study uses reported values directly, as data were available from 2018:Q3 even though the sample includes observations only from 2018:Q4 onward	ϑ
GDPGrowth	The variable is equal to banks' own country GDP growth. In contrast to Novotny-Farkas et al. (2024), who used S&P Global Market Intelligence, this study relies on Eurostat (2024) as the data source.	τ
ΔWUI_t	The variable represents the quarterly change in the World Uncertainty Index (WUI), which measures the frequency of the term "uncertainty" in Economist Intelligence Unit country reports, normalized by the total number of words in each report. The index captures country-level economic and political uncertainty and enables consistent cross-country comparisons. To calculate the quarterly change, the most recent available monthly WUI values are aggregated for each quarter. If data from the prior quarter are unavailable for a country, the second most recent quarter is used. If the change still cannot be computed due to missing values, the European average WUI change is used as a proxy. This imputation ensures complete data coverage across all observations and preserves consistency in the panel structure. Data source: World Uncertainty Index (Ahir et al., 2018).	τ

Variable	Description	C
CBC_t	The variable is defined as the average of the OECD Composite Consumer Confidence and Composite Business Confidence indicators for each bank's home country. For Norway and Romania, where composite consumer confidence data is unavailable, only the business confidence component is used. In cases where country-specific business confidence data is also missing, the CBC value is imputed using the average CBC across all European countries for the corresponding period. Data source: Organisation for Economic Co-operation and Development (2024).	τ

4.2.1 Dependent Variable

This analysis considers four dependent variables, consistent with the approach used by Novotny-Farkas et al. (2024). The first dependent variable is the amount of impairment provisioning on financial assets. To control for differences in bank size, the variable is scaled by total assets at the beginning of each quarter, resulting in the measure $\%Imp_t$. The remaining three variables represent quarterly changes in allowances for credit losses by stage ($ACLS1_t$, $ACLS2_t$ and $ACLS3_t$) also scaled by beginning-of-quarter total assets.

The distinction in naming reflects the underlying accounting treatment. According to Novotny-Farkas et al. (2024), impairment provisions are a flow measure that captures additions to expected credit losses recognized during the period, while ACLs are cumulative stock measures. Therefore, the stage-level dependent variables are labelled as Δ%ACLs to reflect that they capture the period-over-period changes in ACLs, which constitute the flow derived from the underlying stock. Conceptually, Δ%ACLs can be viewed as approximating the same underlying construct as $\%Imp_t$ but measured separately for each impairment stage.

4.2.2 Discretionary Behaviour

To capture discretionary behaviour (β & γ), variables are included to proxy for income smoothing and capital management as described in sections 3.1 and 3.2. The data source for these variables is EBA's Transparency Exercise (European Banking Authority, 2024a) and both variables are constructed in the same manner as by Novotny-Farkas et al. (2024) to ensure consistency.

First, income smoothing is measured using the ratio of earnings before taxes and impairment provisions, scaled by total assets at the beginning of the quarter (%EBImpt). A negative relationship between pre-provisioning income and provisions has been acknowledged as a sufficient proxy for earnings smoothing by European Central Bank (2024a, p.

6–7). This variable and its association with the dependent variables are used to address Research Question 1, which concerns income smoothing.

Second, capital management is accounted for with a dummy variable LOW $CET1_{t-1}$, which has a value of 1 for banks in the lowest quartile of Common Equity Tier 1 (CET1) before allowances for credit losses (ACL), and 0 for all others. Similar binary variables have been used in the literature also prior. For example, Bischof et al. (2021) apply a comparable measure to analyse the link between loan loss adjustments and regulatory capital[7]. This variable and its association with the dependent variables are used to address Research Question 2, which concerns capital management.

4.2.3 Regulatory Expected Credit Loss

Regulatory expected credit losses (δ) are proxied using two variables: $\%CRWA_{t-1}$ and %ΔECL. Data source for both variables is EBA's Transparency Exercise (European Banking Authority, 2024a) but %ΔECL utilizes data also from EBA's Risk Dashboard (European Banking Authority, 2024b).

The former of the two variables represents the bank's credit risk-weighted (CRWA) at the beginning of the quarter, scaled by total assets. This variable is constructed to follow the approach used by Novotny-Farkas et al. (2024) as closely as possible.

The second proxy, %ΔECL, captures the change in estimated expected credit losses regulatory risk parameters. To evaluate the timing of loss recognition, the model includes values for the previous, current, and subsequent quarters, expressed as $\sum_{\{t-1\}}^{\{t+1\}} \Delta ECL$. Although this variable is based on the same methodology as in Novotny-Farkas et al. (2024), minor deviations may occur due to uncertainties around its construction.

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[7] Bischof et al. (2021) use cross-sectional data from banks participating in the ECB's 2014 Asset Quality Review and find that banks with lower regulatory capital are more strongly associated with overvaluation of loan portfolios.

EBA's risk dashboard (European Banking Authority, 2024b), and thereby this study, lacks the key risk indicator (KRI) data of PD and LGD values for Bulgaria and Slovenia under the Corporates - Specialised Lending (IRB) portfolio. However, KRI data is available for other portfolios in these countries. To address this gap, the average values from all other European countries are used for the missing portfolio-specific KRIs. Similarly, median PD data is unavailable for Denmark in the following portfolios: Retail - Secured on real estate property, Retail - Qualifying Revolving, and Retail - Other Retail. As with the previous case, the average values from all other European countries are used to fill in the missing data. It is unclear whether these differences stem from variations in sample composition, differences in between the KRI datasets or from differences in variable construction methodologies.

4.2.4 Indicators of Credit Risk Stage

Multiple variables are used as indicators of credit risk stage (θ). All of these are constructed same way as by Novotny-Farkas et al. (2024) and the data source is EBA's Transparency Exercise (European Banking Authority, 2024a).

First, quarterly change in financial assets scaled by beginning of quarter total assets ($\Delta FinAssets_t$) and financial assets at the beginning of quarter scaled by total assets ($FinAssets_{t-1}$) represent the scope of financial assets subject to ECL estimation, as IFRS 9 requires recognition of expected credit losses already at initial recognition.

To capture the impact of a SICR, the variable ΔExp30Dayst measures the change in performing exposures with contractual payments between 30 and 90 days past due[8], while quarterly change in performing exposures with forbearance measures (ΔExpForbt) serves as an alternative proxy for SICR, consistent with supervisory expectations that

[8] If a contract is 90 days past due, it is considered defaulted.

forbearance should act as a backstop for identifying significant increases in credit risk (Novotny-Farkas et al., 2024, p. 15).

Finally, quarterly change in non-performing exposures scaled by total assets (ΔNPE_t) is included to proxy for stage 3 loans, reflecting the similarity between the credit-impaired definition under IFRS 9 and the prudential definition of default (Behn & Cyril, 2023, p. 11). These variables and their association to dependent variables is to be used for answering to RQ3.

4.2.5 Other Loan Portfolio Characteristics and Size

Multiple variables are included for capturing other loan portfolio characteristics (μ). EBA's Transparency Exercise (European Banking Authority, 2024a) serves as the data source for each of the variables and all but the size variable are constructed similarly to Novotny-Farkas et al. (2024).

First, the total amount of collateral received on non-performing exposure (NPE)s, scaled by the total amount of NPEs ($Collateralized_t$) is introduced and used to control for credit risk mitigation techniques and exposure-type heterogeneity (Novotny-Farkas et al., 2024, pp. 15–16). Second, to further control for differences in exposure types, the variables $InstExp_t$, $CorpExp_t$, $RetExp_t$, and $SMEExp_t$ are included. These reflect institutional, corporate, retail, and SME exposures, respectively.

Finally, bank size (ϑ) is controlled for using the variable $Size_{t-1}$, which is defined as the natural logarithm of total assets at the beginning of the quarter. Unlike Novotny-Farkas et al. (2024), who inferred missing 2018:Q4 total assets using the EAD-to-total-assets ratio, this study uses reported values directly, as data were available from 2018:Q3 even though the sample includes observations only from 2018:Q4 onward.

4.2.6 Macroeconomic Indicators

Ultimately, as one of the key aims of IFRS 9 ECL framework has been to incorporate forward-looking information (FLI) to the estimates (European Banking Authority, 2017), macroeconomic variables are included in the model (τ). The GDP Growth Forecast variable is the only one constructed identically to Novotny-Farkas et al. (2024a), using the same data and methodology. Due to this study opting to use only publicly available data, the others differ. Moreover, the data source differs between each variable.

The variables GDPGrowth and GDPForGrowth capture current GDP growth and the forecasted GDP growth over the next four quarters, respectively. Current GDP growth data are sourced from Eurostat (2024), while GDP growth forecasts are obtained from the European Central Bank (2024c).

The variable ΔWUIt is included as a substitute for $SOVCDS_t$ used by Novotny-Farkas et al. (2024). It represents the changes in economic uncertainty with a one-quarter lag by measuring the quarterly change in the frequency of the term "uncertainty" being used in Economist Intelligence Unit country reports (Ahir et al. 2018). Finally, average of the OECD Composite Consumer Confidence and Business Confidence indexes (CBC_t) is used in place of the OECD Composite Leading Indicator (CLI_t) as an alternative proxy for cyclical macroeconomic dynamics.

These macroeconomic variables and their association to dependent variables is to be used for answering to RQ4. The substitute variables are discussed more comprehensively in Section 4.2.8 in relation to the variables used by Novotny-Farkas et al. (2024).

4.2.7 Descriptive Statistics

Descriptive statistics for all variables used in the empirical analysis are presented in Table 4. The summary includes the mean, standard deviation, 25th percentile (P25), median, 75th percentile (P75), minimum, and maximum values for each variable. These statistics are calculated using the full sample of quarterly observations, offering a comprehensive overview of the distribution and variation in the dataset. This overview provides context for interpreting the regression results and ensures transparency regarding the structure and characteristics of the underlying data.

Table 4. Descriptive Statistics for Variables used in the Analysis.

Variable	**Mean**	**SD**	**P25**	**Median**	**P75**	**Min**	**Max**
%Impt*t*	0.057	0.093	0.006	0.032	0.082	-0.116	0.546
%ΔACLS1$_t$	0.003	0.027	-0.005	0.000	0.007	-0.089	0.126
%ΔACLS2$_t$	0.004	0.039	-0.009	0.000	0.011	-0.119	0.177
%ΔACLS3$_t$	-0.050	0.208	-0.035	-0.001	0.014	-1.430	0.218
%EBImpt*t*	0.258	0.210	0.126	0.215	0.365	-0.322	0.929
LOW CET1$_{t-1}$	0.254	0.436	0.000	0.000	1.000	0.000	1.000
CRWA$_{t-1}$	0.400	0.146	0.296	0.371	0.492	0.056	0.783
ΔECL$_{t+1}$	0.004	0.018	-0.003	0.001	0.009	-0.050	0.086
ΔECL$_t$	0.004	0.019	-0.004	0.001	0.009	-0.056	0.086
ΔECL$_{t-1}$	0.003	0.018	-0.004	0.001	0.009	-0.057	0.084
ΔFinAssets$_t$	0.006	0.026	-0.007	0.005	0.018	-0.070	0.100
FinAssets$_{t-1}$	0.745	0.159	0.693	0.781	0.847	0.116	0.964
ΔExp30Days$_{t+1}$	-0.005	0.109	-0.031	-0.001	0.025	-0.445	0.411
ΔExp30Days*t*	-0.004	0.109	-0.030	0.000	0.026	-0.445	0.411
ΔExp30Days$_{t-1}$	-0.003	0.110	-0.030	0.000	0.027	-0.457	0.424
ΔExpForb$_{t+1}$	-0.009	0.211	-0.058	-0.008	0.028	-0.821	0.991
ΔExpForb*t*	-0.014	0.214	-0.062	-0.009	0.026	-0.847	0.975
ΔExpForb$_{t-1}$	-0.020	0.225	-0.066	-0.010	0.024	-1.003	0.975
ΔNPE$_{t+1}$	-0.076	0.332	-0.090	-0.013	0.034	-2.181	0.631
ΔNPE$_t$	-0.098	0.380	-0.104	-0.016	0.030	-2.438	0.608
ΔNPE$_{t-1}$	-0.122	0.434	-0.116	-0.020	0.028	-2.808	0.606
Collateralized$_t$	0.431	0.204	0.290	0.412	0.552	0.000	1.038
InstExp$_{t-1}$	0.091	0.091	0.035	0.061	0.110	0.006	0.511
CorpExp$_{t-1}$	0.247	0.144	0.141	0.227	0.333	0.003	0.667
RetExp$_{t-1}$	0.239	0.196	0.073	0.193	0.367	0.000	0.828
SMEExp$_{t-1}$	0.129	0.096	0.055	0.113	0.186	0.000	0.470
Size$_{t-1}$	11.485	1.452	10.675	11.337	12.472	8.269	14.586
GDPGrowth$_t$	0.004	0.033	-0.001	0.003	0.010	-0.123	0.144
GDPForGrowth$_{t+1\text{-}4}$	1.875	2.891	0.700	1.100	1.800	-2.800	12.700
WUI$_t$	0.159	0.723	-0.281	-0.013	0.301	-0.722	2.892
ΔCBC$_t$	99.827	1.358	98.885	99.735	100.774	96.443	102.870

Note: All statistics are based on N = 2,266 observations.

To better understand the data used in this study, Table 5 compares key descriptive statistics between the baseline period used by Novotny-Farkas et al. (2024) and the extended period analysed in this study[9]. The table reports the mean and standard deviation for each variable across both periods, along with the difference in means. Statistically significant differences, based on standard t-tests, are marked with asterisks. The comparison highlights how the economic environment has changed over time, with the extended period reflecting lower uncertainty, slower GDP growth, and declining confidence indicators, as shown in Figure 5 and Figure 6. These differences are important for interpreting the results of the regression analysis, as they may influence how banks respond to macro-financial conditions when recognizing impairment provisions.

Table 5. Comparison of Variables Between Benchmark and Sample.

	Scope				
	2022		**2024**		
Variable	**Mean**	**SD**	**Mean**	**SD**	**Diff. Means**
$\%Impt_t$	0.065	0.105	0.044	0.063	-0.0209***
$\%EBImpt_t$	0.004	0.029	0.001	0.025	-0.0023**
$\%\Delta ACLS1_t$	0.004	0.043	0.002	0.031	-0.0024
$\%\Delta ACLS2_t$	-0.073	0.250	-0.007	0.071	0.0654***
$\%\Delta ACLS3_t$	0.216	0.200	0.335	0.207	0.1193***
$LOW\ CET1_{t-1}$	0.255	0.436	0.253	0.435	-0.0016
$CRWA_{t-1}$	0.413	0.153	0.377	0.131	-0.0355***
ΔECL_{t+1}	0.006	0.019	0.001	0.017	-0.0046***
ΔECL_t	0.005	0.019	0.001	0.018	-0.0045***
ΔECL_{t-1}	0.005	0.018	0.001	0.019	-0.0038***
$\Delta FinAssets_t$	0.007	0.028	0.006	0.024	-0.001
$FinAssets_{t-1}$	0.753	0.154	0.730	0.169	-0.0226***
$\Delta Exp30Days_{t+1}$	-0.007	0.111	-0.001	0.104	0.0064
$\Delta Exp30Days_t$	-0.008	0.112	0.004	0.101	0.0121***
$\Delta Exp30Days_{t-1}$	-0.009	0.116	0.007	0.099	0.0164***
$\Delta ExpForb_{t+1}$	0.004	0.227	-0.034	0.174	-0.0379***
$\Delta ExpForb_t$	0.002	0.227	-0.042	0.183	-0.0436***
$\Delta ExpForb_{t-1}$	-0.001	0.233	-0.055	0.206	-0.0547***
ΔNPE_{t+1}	-0.117	0.387	-0.001	0.168	0.1163***
ΔNPE_t	-0.147	0.448	-0.008	0.166	0.1394***
ΔNPE_{t-1}	-0.176	0.510	-0.021	0.197	0.155***

[9] As discussed in Chapter 4.1.2, the baseline period is 2018Q4 - 2022Q2 while the data used in this study prolongs until 2024Q2.

	Scope				
	2022		2024		
Variable	**Mean**	**SD**	**Mean**	**SD**	**Diff. Means**
Collateralized$_t$	0.423	0.197	0.445	0.214	0.0227**
InstExp$_{t-1}$	0.095	0.093	0.084	0.086	-0.0108***
CorpExp$_{t-1}$	0.246	0.142	0.249	0.146	0.0028
RetExp$_{t-1}$	0.246	0.196	0.225	0.195	-0.0211**
SMEExp$_{t-1}$	0.129	0.095	0.128	0.097	-0.0011
Size$_{t-1}$	11.465	1.473	11.522	1.411	0.0575
GDPGrowth$_t$	0.005	0.040	0.002	0.008	-0.0028**
GDPForGrowth$_{t+1\text{-}4}$	2.598	3.352	0.534	0.515	-2.0645***
ΔWUI$_t$	0.248	0.823	-0.005	0.441	-0.2532***
CBC$_t$	100.302	1.329	98.946	0.890	-1.3567***

To complement the descriptive overview of regression variables, Table 8 and Table 9 in the Appendix provide detailed statistics for the underlying loss given default (LGD) and probability of default (PD) parameters. These parameters are used in the computation of regulatory expected loss measures and are reported by regulatory region and exposure class. Including these additional breakdowns helps to illustrate the variability in credit risk inputs across portfolios and jurisdictions, thereby enhancing transparency in how forward-looking risk factors are incorporated into the empirical framework.

4.2.8 Comparison to Prior Research

Although study builds on the empirical framework developed by Novotny-Farkas et al. (2024), it applies it to a structurally different macro-financial context. Most notably, it extends the analysis period from 2022:Q2 to 2024:Q2, a time period characterized by positive and sharply rising interest rates, subdued GDP growth, and relatively stable economic conditions. This setting stands in stark contrast to the earlier study's focus on the post-crisis low-interest rate environment and the COVID-19 period, offering a unique opportunity to reassess the determinants of impairment provisioning under more normalized monetary conditions.

Building on this shift in context, the study introduces several methodological enhancements, particularly in the construction and sourcing of macroeconomic variables. These adjustments are motivated by a commitment to transparency and replicability.

The first departure concerns the measurement of GDP growth. Whereas Novotny-Farkas et al. (2024, pp. 62–63) rely on proprietary data from S&P Global Market Intelligence, this study uses harmonized quarterly national accounts published by Eurostat (Eurostat, 2024). This publicly accessible source ensures consistent cross-country comparability and facilitates full replication.

Second, prior research often uses sovereign credit default swap (SOVCDS) spreads as a proxy for country-level macroeconomic risk (e.g., Novotny-Farkas et al. 2024 & Lopez-Espinosa, Ormazabal, and Sakasai 2021), reflecting market perceptions of sovereign creditworthiness. However, the validity of this proxy has been questioned. Longstaff, Pan, Pedersen, and Singleton (2011, p. 98–99) show that SOVCDS spreads are driven more by global market factors such as US equity and high-yield factors, volatility risk premiums (VIX index), and liquidity conditions than by country-specific fundamentals, potentially undermining their usefulness in cross-country studies. To address these limitations, this study replaces Sovereign Credit Default Swap (SOVCDS) with the World Uncertainty Index (WUI), which captures political and economic uncertainty based on country-specific textual analysis from Economist Intelligence Unit reports (Ahir et al., 2018). The WUI provides broad country coverage and is a publicly available proxy for macro-financial uncertainty (Ahir, Bloom, & Furceri, 2022), making it a more robust and interpretable input for assessing banks' forward-looking provisioning behaviour. Moreover, unlike SOVCDS (Longstaff et al., 2011, p. 75–81), the WUI shows only a weak association with the VIX index, suggesting that it better isolates country-specific uncertainty Ahir et al. (2022, p. 12).

Third, the measurement of forward-looking macroeconomic expectations is adapted. Given the incomplete country coverage of the OECD Composite Leading Indicator (CLI) in publicly available datasets, we construct an alternative based on the average of the OECD's Composite Business and Consumer Confidence indices, available on OECD Data Explorer (2024). This proxy offers broader sample coverage while capturing comparable sentiment dynamics.

Together, these changes represent a deliberate move toward publicly available and broadly applicable data sources. By relying exclusively on open indicators (Eurostat GDP, the WUI, and OECD sentiment measures) this study not only improves the reproducibility of its findings but also facilitates future extensions of the analysis. More importantly, these design choices position the study to examine whether the discretionary provisioning patterns identified by Novotny-Farkas et al. (2024) persist in a qualitatively different monetary and economic environment.

4.3 Methodology

The empirical model employed in this study is based on the loan loss determinants framework introduced by Novotny-Farkas et al. (2024, pp. 13–15), which is specifically designed to capture the discretionary and non-discretionary drivers of impairment provisions under the IFRS 9 ECL model.

In their paper, Novotny-Farkas et al. (2024, p. 3) cite a forthcoming chapter in the Oxford Handbook of Banking authored by Beatty, Liao, and Wu (2023), of which a preliminary version is available, arguing that much of the prior literature on banks' provisioning behaviour was developed under the IL model and therefore the metrics used are not necessarily fully appropriate for analysing provisions under the ECL) framework.

For example, under the IL model, assessments of provisioning timeliness predominantly focus the relationship between provisions and subsequent-period non-performing loans (Beatty et al., 2023, p. 12–13, 20). On the contrary, as ECL framework is a more forward-looking approach and requires provisioning to account also for anticipated potential future losses, relying solely on next period non-performing loans may not sufficiently capture provisioning timeliness under the ECL model. The issue is the most prominent on Stage 2 and 3 provisions, which account for lifetime losses rather than the next 12-months (Beatty et al., 2023, p. 16).

To account for the issues of comparability of measurement for IL and ECL models, Novotny-Farkas et al. (2024) developed an extended model to incorporate specific features of IFRS 9 and ECL models for analysing the impairment determinants.

The new specification retains many of the same variables as the commonly used Incurred Loan Loss Determinants model (Beatty and Liao, 2014; Bushman and Williams, 2012), when applied under the IFRS 9, which the authors estimated alongside their extended regression framework (Novotny-Farkas et al., 2024, p. 67–72). In both models, $\%Impt_t$ can be used as a dependent variable although its meaning has inherently changed amid the transition from IL to ECL framework. However, in the new Impairment Provisioning Determinants model, also changes in the ACL by stage can be used. Additionally, ΔNPE_{t+1}, ΔNPE_t, ΔNPE_{t+1}, $Size_{t-1}$ and $GDPGrowth_t$ are used in both models.

The only variable dropped from the Incurred Loan Loss Determinants model is $BCAP_{t-1}$, which measures the amount of CET1 before ACL, scaled with total assets (Novotny-Farkas et al., 2024, p. 71–71). In the new model, it is replaced with a very similar but binary variable $LOWCET1_{t-1}$, as defined in Table 2. The variable is likely transformed to binary form, for better capturing the non-linear effect of regulatory capital rules imposing hard minimums.

In addition to incorporating most variables from the Incurred Loan Loss Determinants model, several new variables were introduced by the authors. Specifically, regulatory expected variables, such as $CRWA_{t-1}$ and ΔECL, were included to reflect the alignment between the IFRS 9 ECL framework and regulatory credit risk modelling (Novotny-Farkas et al., 2024, pp. 14–15). As discussed in Section 2.4 and in earlier work by Novotny-Farkas

(2016, pp. 204–205), the IFRS 9 ECL provisioning approach exhibits greater similarity to regulatory credit risk modelling than previous standards, thereby enabling banks to utilize regulatory measures and models within their IFRS 9 ECL frameworks.

Second, (Novotny-Farkas et al., 2024, p. 15) introduce indicators of credit risk stage. These variables include granular proxies for assets by stage, instead of considering only non-performing exposures, which under IFRS 9 in practice are nearly aligned to the definition of credit impaired assets that are to be sorted to stage 3 (European Banking Authority, 2021, p. 36).

Third, to capture the effects of mitigation techniques and different exposure types, Novotny-Farkas et al. (2024, p. 15 to 16) introduce variables for other loan portfolio characteristics. This represents another significant improvement since studies under the IL framework generally relied on measures aggregated across all loan categories (Beatty et al., 2023, p. 12 to 13). Under IFRS 9 mitigation techniques must directly influence provisioning as European Banking Authority (2017, p. 21 to 23, 50) explain that sound credit risk methodologies include consideration of mitigants such as the impact of collateral on ECL and that supervisors should take this into account when evaluating banks' approaches to measuring ECL.

Finally, Novotny-Farkas et al. (2024, p. 16) incorporate new macroeconomic variables that capture forward looking information which, as already discussed, ECL estimates must reflect. Moreover, European Banking Authority (2017, p. 18) stress that including forward looking macroeconomic factors is a prerequisite for recognizing credit losses in a timely manner.

Equation 2 presents the complete empirical impairment model developed by Novotny-Farkas et al. (2024) and re-estimated in this analysis. The specification is estimated by ordinary least squares (OLS) on the sample described in Section 4.1. The model formula is constructed without the inclusion of fixed or random effects. Prior to estimation, all dependent and independent variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Definitions and data sources for each covariate block—Smoothing, Capital Management, Regulatory Expected Loss, Indicators of Credit Risk Stage, Other Loan Portfolio Characteristics, Size, and Macro Indicators—are provided in Chapter 4.1.

$$\begin{aligned} \%Imp \ =\ \alpha +\ \beta Earnings\ Smoothing\ +\ \gamma Capital\ Management \\ +\ \delta Regulatory\ expected\ loss +\ \theta Indicators\ of\ credit\ risk\ stage \\ +\ \mu Other\ loan\ portfolio\ characteristics\ +\ \vartheta Size\ +\ \tau Macro\ indicators\ +\epsilon \end{aligned} \quad (2)$$

The re-estimation of this model enables an evaluation of the influence of impairment provisioning determinants on banks' IFRS 9 ECL provisioning behaviour. It directly addresses the study's overarching research questions regarding whether prior evidence of discretionary provisioning, including income smoothing (Hypothesis H1), capital management (Hypothesis H2), delayed loss recognition (Hypothesis H3), and the procyclical responsiveness of provisions for unimpaired assets (Hypothesis H4), persists over an extended observation period.

To guide the empirical analysis, four hypotheses are formulated, each corresponding to a specific aspect of discretionary provisioning behaviour:

$$\begin{aligned} &H1: Regression\ coefficient\ of\ quarterly\ net\ income\ before\ taxes \\ &\quad and\ impairment\ provisions\ \ (\%EBImp_t)\ is\ positive\ (\beta >\ 0) \end{aligned} \quad (3)$$

$$\begin{aligned} &H2: Regression\ coefficient\ of\ the\ indicator\ for\ banks\ with\ CET1 \\ &\quad in\ the\ lowest\ quartile\ \left(LOW\ CET1_{\{t-1\}}\right)\ is\ negative\ (\gamma <\ 0) \end{aligned} \quad (4)$$

$$\begin{aligned} &H3: Regression\ coefficient\ of\ quarterly\ change\ in\ non\text{-}performing \\ &\quad exposures\ (\Delta NPE_t)\ is\ positive\ (\theta >\ 0) \end{aligned} \quad (5)$$

$$\begin{aligned} &H4: Regression\ coefficient\ of\ a\ macroeconomic \\ &\quad indicator_i\ is\ negative\ (\tau <\ 0) \end{aligned} \quad (6)$$

To validate the accuracy of the variable construction, data reconciliation, and model implementation in this study, the regression model presented in Equation 2 is first estimated over the sample period 2018:Q4 to 2022:Q2, consistent with the period used by

Novotny-Farkas et al. (2024). This re-estimation primarily serves to confirm that the variables and model specification are appropriately aligned with prior work. Subsequently, the model is re-estimated using a prolonged sample period ending in 2024:Q2, enabling an evaluation of whether the key findings reported by Novotny-Farkas et al. (2024) persist when a broader and more recent dataset is considered.

Section 4.4 presents the empirical findings derived from testing these hypotheses. Chapter 4.4.1 reports the main regression results, while Chapter 4.4.2 compares the estimated results across different sample periods and benchmarks, focusing primarily on the comparison with Novotny-Farkas et al. (2024), but also evaluating the persistence and robustness of the findings over an extended observation period.

4.4 Results and Findings

This chapter presents the empirical results of the study, focusing on testing the hypotheses formulated in Section 4.3. Subsection 4.4.1 first re-estimates the model over the original sample period used by Novotny-Farkas et al. (2024) to verify the reliability of the variable construction and model implementation, and then evaluates each hypothesis individually based on the full-sample estimates. Subsection 4.4.2 compares the findings to those of earlier studies, particularly Novotny-Farkas et al. (2024), to assess the persistence of key empirical relationships when tested over an extended and more recent observation period.

4.4.1 Empirical Results

As discussed in Chapter 4.2.7, the model is first estimated over the period used by Novotny-Farkas et al. (2024) to validate the variable construction, data reconciliation, and model implementation. Table 6 presents the estimated coefficients and corresponding standard errors (in parentheses). Statistical significance is indicated by asterisks and summary statistics, including the number of observations, R^2 values, residual standard error and the F-statistic are reported at the end of the table. The results show that the estimated R2 values and the signs and significance of key coefficients are closely aligned with those reported by Novotny-Farkas et al. (2024, p. 47, Table 4). The number of observations in the re-estimated sample (1,472) is slightly higher than that reported by Novotny-Farkas et al. (2024) (1,432), likely reflecting minor differences in data reconciliation or sample filtering procedures. However, this discrepancy is small and does not materially affect the overall validation outcomes.

Table 6. Determinants of Impairment Provisions: Benchmark Sample.

	Dependent Variable			
	$\%Impt_t$	$\Delta ACLS1_t$	$\Delta ACLS2_t$	$\Delta ACLS3_t$
	(1)	(2)	(3)	(4)
$\%EBImpt_t$	0.078***	0.016***	0.018***	0.015
	(0.013)	(0.004)	(0.006)	(0.017)
LOW $CET1_{t-1}$	0.004	-0.001	-0.004	0
	(0.005)	(0.002)	(0.003)	(0.007)
$CRWA_{t-1}$	0.147***	-0.008	0.006	-0.089***
	(0.021)	(0.007)	(0.01)	(0.027)
ΔECL_{t+1}	0.156	0.134***	0.002	-0.121
	(0.122)	(0.04)	(0.058)	(0.154)
ΔECL_t	0.11	0.152***	0.068	-0.187
	(0.126)	(0.041)	(0.06)	(0.16)
ΔECL_{t-1}	0.227*	0.004	-0.014	0.043
	(0.128)	(0.042)	(0.061)	(0.162)
$\Delta FinAssets_t$	-0.164*	0.119***	0.032	-0.123
	(0.089)	(0.029)	(0.042)	(0.113)
$FinAssets_{t-1}$	0.076***	0.001	0.018**	0.016
	(0.016)	(0.005)	(0.008)	(0.021)
$\Delta Exp30Days_{t+1}$	-0.015	-0.009	0.008	0.017
	(0.021)	(0.007)	(0.01)	(0.027)
$\Delta Exp30Days_t$	-0.059***	-0.003	0.035***	-0.047*
	(0.021)	(0.007)	(0.01)	(0.027)
$\Delta Exp30Days_{t-1}$	-0.005	-0.004	-0.014	-0.035
	(0.02)	(0.007)	(0.01)	(0.025)
$\Delta ExpForb_{t+1}$	0.031***	0.002	0.005	-0.044***
	(0.01)	(0.003)	(0.005)	(0.013)
$\Delta ExpForb_t$	-0.021*	-0.003	0.035***	0.005
	(0.011)	(0.004)	(0.005)	(0.014)
$\Delta ExpForb_{t-1}$	0.004	-0.004	-0.001	-0.035***

	Dependent Variable			
	%Impt$_t$	ΔACLS1$_t$	ΔACLS2$_t$	ΔACLS3$_t$
	(1)	(2)	(3)	(4)
	(0.01)	(0.003)	(0.005)	(0.013)
ΔNPE_{t+1}	-0.036***	0.001	0.008***	0.006
	(0.007)	(0.002)	(0.003)	(0.008)
ΔNPE_t	-0.052***	0.001	0.013***	0.519***
	(0.006)	(0.002)	(0.003)	(0.008)
ΔNPE_{t-1}	-0.031***	-0.001	-0.007***	-0.016**
	(0.005)	(0.002)	(0.002)	(0.007)
Collateralized$_t$	0.031**	0.003	-0.004	-0.045***
	(0.013)	(0.004)	(0.006)	(0.017)
InstExp$_{t-1}$	0.004	0.009	0	-0.034
	(0.027)	(0.009)	(0.013)	(0.034)
CorpExp$_{t-1}$	0.014	0.005	-0.004	-0.033
	(0.019)	(0.006)	(0.009)	(0.024)
RetExp$_{t-1}$	-0.027**	0	-0.008	-0.031*
	(0.013)	(0.004)	(0.006)	(0.017)
SMEExp$_{t-1}$	-0.008	0.007	0	0.01
	(0.028)	(0.009)	(0.013)	(0.035)
Size$_{t-1}$	0.011***	-0.001	0.002*	-0.001
	(0.002)	(0.001)	(0.001)	(0.003)
GDPGrowth$_t$	-0.25***	-0.053***	-0.064**	0.099
	(0.06)	(0.02)	(0.028)	(0.076)
GDPForGrowth$_{t+1\text{-}4}$	0.003***	0	0.002***	-0.001
	(0.001)	(0)	(0)	(0.001)
Δ%WUI$_t$	-0.005*	0	-0.003**	-0.004
	(0.003)	(0.001)	(0.001)	(0.003)
CBC$_t$	-0.021***	-0.003***	-0.007***	-0.003
	(0.002)	(0.001)	(0.001)	(0.002)
Intercept	1.879***	0.268***	0.639***	0.392
	(0.194)	(0.063)	(0.092)	(0.246)
Observations	1,472	1,472	1,472	1,472
R2	0.369	0.108	0.168	0.822
Adjusted R2	0.358	0.091	0.153	0.818
Res. Std. Error (df = 1444)	0.084	0.027	0.040	0.107
F Statistic (df = 27; 1444)	31.331***	6.483***	10.817***	246.433**
Note:			*p<0.1; **p<0.05; ***p<0.01	

Minor differences are nevertheless observed. Notably, the capital management proxy (LOW CET1$_{t-1}$) loses its statistical significance across all model specifications in this study, whereas Novotny-Farkas et al. (2024) reported a significant association with Stage 2 allowances[10]. In terms of explanatory power, the adjusted R2 for the overall impairment rate model (%Imptt) is slightly improved in this study (0.36 versus 0.35 in Novotny-Farkas et al. (2024)). For Stage 1 and Stage 2 allowances, the adjusted R2 values are also marginally higher (0.09 versus 0.08 for Stage 1 and 0.15 versus 0.12 for Stage 2). By contrast, for Stage 3 allowances, the adjusted R2 is modestly lower (0.82 in this study compared to 0.85 reported by Novotny-Farkas et al. (2024)). Overall, the explanatory power of the models remains closely aligned, providing additional reassurance regarding the validity of the variable construction and model implementation.

These minor differences do not materially affect the ability of the re-estimated models to replicate the findings of Novotny-Farkas et al. (2024). Overall, the validation objectives are considered successfully achieved, supporting the reliability of the subsequent full-sample analysis.

Table 7 reports coefficient estimates from four pooled OLS regressions of Equation 2. Each column corresponds to a different dependent variable: Column (1) uses the overall impairment rate (%$Impt_t$), while Columns (2) to (4) use the changes in Stage 1, Stage 2 and Stage 3 allowances, respectively. For each specification, estimated coefficients are accompanied by standard errors in parentheses and statistical significance is indicated by asterisks. The bottom panel presents key diagnostics, including the number of observations, R2, adjusted R2, residual standard error and F-statistic, all based on the full sample of 2,266 quarterly bank-level observations.

Table 7. Determinants of Impairment Provisions: Full Sample.

	Dependent Variable:			
	%$Impt_t$	$\Delta ACLS1_t$	$\Delta ACLS2_t$	$\Delta ACLS3_t$
	(1)	(2)	(3)	(4)
%$EBImpt_t$	0.051***	0.005	0.009**	-0.004
	(0.009)	(0.003)	(0.004)	(0.011)

[10] This change may reflect the sensitivity of quartile-based indicators like LOW $CET1_{t-1}$, which equals one for banks in the lowest quartile of $CET1_{t-1}$ each quarter. Minor sample differences can shift banks across quartiles, affecting classification and statistical significance.

	Dependent Variable:			
	%Impt$_t$	ΔACLS1$_t$	ΔACLS2$_t$	ΔACLS3$_t$
	(1)	(2)	(3)	(4)
LOW CET1$_{t-1}$	0.006	-0.001	-0.003	0.003
	(0.004)	(0.001)	(0.002)	(0.005)
CRWA$_{t-1}$	0.138***	-0.001	0.004	-0.06***
	(0.016)	(0.005)	(0.008)	(0.019)
ΔECL$_{t+1}$	0.181*	0.12***	0.019	-0.003
	(0.092)	(0.031)	(0.044)	(0.11)
ΔECL$_t$	0.22**	0.147***	0.145***	-0.069
	(0.094)	(0.032)	(0.045)	(0.112)
ΔECL$_{t-1}$	0.219**	-0.015	0.05	-0.073
	(0.092)	(0.031)	(0.044)	(0.11)
ΔFinAssets$_t$	-0.067	0.141***	0.036	-0.027
	(0.069)	(0.023)	(0.033)	(0.082)
FinAssets$_{t-1}$	0.064***	-0.001	0.013**	-0.002
	(0.012)	(0.004)	(0.005)	(0.014)
ΔExp30Days$_{t+1}$	-0.018	-0.004	0.007	-0.009
	(0.016)	(0.005)	(0.008)	(0.019)
ΔExp30Days$_t$	-0.041**	-0.003	0.033***	-0.053***
	(0.016)	(0.006)	(0.008)	(0.019)
ΔExp30Days$_{t-1}$	-0.001	-0.005	-0.006	-0.045**
	(0.016)	(0.005)	(0.008)	(0.019)
ΔExpForb$_{t+1}$	0.035***	0.004	0.003	-0.034***
	(0.008)	(0.003)	(0.004)	(0.01)
ΔExpForb$_t$	-0.017**	-0.004	0.032***	0.01
	(0.009)	(0.003)	(0.004)	(0.01)
ΔExpForb$_{t-1}$	0.001	-0.001	-0.003	-0.016*
	(0.008)	(0.003)	(0.004)	(0.009)
ΔNPE$_{t+1}$	-0.037***	0	0.007***	0.002
	(0.006)	(0.002)	(0.003)	(0.007)
ΔNPE$_t$	-0.051***	0.001	0.012***	0.501***
	(0.005)	(0.002)	(0.003)	(0.006)
ΔNPE$_{t-1}$	-0.033***	-0.001	-0.008***	-0.012**
	(0.005)	(0.002)	(0.002)	(0.005)
Collateralized$_t$	0.021**	-0.002	-0.006	-0.053***
	(0.009)	(0.003)	(0.004)	(0.011)
InstExp$_{t-1}$	0.018	0.006	0.005	-0.024
	(0.021)	(0.007)	(0.01)	(0.024)
CorpExp$_{t-1}$	0.008	-0.001	-0.002	-0.036**
	(0.014)	(0.005)	(0.007)	(0.017)
RetExp$_{t-1}$	-0.027***	0.002	-0.002	-0.002
	(0.01)	(0.003)	(0.005)	(0.012)
SMEExp$_{t-1}$	-0.016	0.003	0.008	-0.001

	Dependent Variable:			
	%Impt$_t$	ΔACLS1$_t$	ΔACLS2$_t$	ΔACLS3$_t$
	(1)	(2)	(3)	(4)
	(0.021)	(0.007)	(0.01)	(0.025)
Size$_{t-1}$	0.01***	-0.001	0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.002)
GDPGrowth$_t$	-0.308***	-0.065***	-0.084***	0.101
	(0.054)	(0.018)	(0.026)	(0.064)
GDPForGrowth$_{t+1\text{-}4}$	0.003***	0*	0.002***	-0.001
	(0.001)	(0)	(0)	(0.001)
Δ%WUI$_t$	-0.003	0.001	-0.002*	-0.001
	(0.002)	(0.001)	(0.001)	(0.003)
CBC$_t$	-0.013***	-0.001***	-0.005***	-0.001
	(0.001)	(0)	(0.001)	(0.002)
Intercept	1.076***	0.136***	0.441***	0.218
	(0.144)	(0.049)	(0.068)	(0.17)
Observations	2,266	2,266	2,266	2,266
R2	0.298	0.077	0.126	0.803
Adjusted R2	0.290	0.065	0.116	0.801
Res. Std. Error (df = 1444)	0.078	0.027	0.037	0.093
F Statistic (df = 27; 1444)	35.198***	6.875***	11.984***	338.765***
Note:				*p<0.1; **p<0.05; ***p<0.01

The coefficient of %EBImpt$_t$, which captures earnings smoothing behaviour, is positive and statistically significant when the dependent variables are %EBImpt$_t$ and ΔACLS2$_t$, but not significant for ΔACLS1$_t$ and ΔACLS3$_t$. This finding provides support for Hypothesis H_1, which posits a positive association between pre-income earnings and provisioning behaviour.

The coefficient of LOW CET1$_{t-1}$ is positive but statistically insignificant when LOW, indicating no evidence of capital management behaviour. Similarly, the coefficient remains insignificant across all specifications where the dependent variables are the changes in allowances at different stages (ΔACLS1$_t$, ΔACLS2$_t$, and ΔACLS3$_t$). These findings do not provide support for Hypothesis H_2, which predicts that capital management incentives are associated with lower provisioning by weakly capitalized banks.

The positive and statistically significant coefficient of $CRWA_{t-1}$ supports the close alignment between regulatory credit risk parameters and those applied for IFRS 9 provisioning purposes. Moreover, the economic significance[11] is notable (21.76 %.) The alignment between regulatory risk measures and provisioning behaviour clearly reflected also in the coefficients of the ΔECL variables, particularly for the current quarter (t) and the subsequent quarter ($t + 1$). The combined economic significance of the lagged, current, and subsequent changes in expected credit losses (%ΔECL) is however less significant (12.30 %). Since the ΔECL variables are based on performing exposures, it is expected that their association with the Stage 3 allowance changes is weaker, including non-significant or even negative signs. Although these findings do not directly relate to any of the five hypotheses formulated, they are analysed to better understand the determinants of expected credit losses within the broader framework of the study.

The estimated coefficients for the credit risk stage indicators are broadly in line with expectations. Changes in financial exposures ($\Delta FinAssets_t$) are strongly associated with changes in ACL_t for stage 1 exposures but exhibit weaker relationships with allowances for other stages and with overall impairment provisions. The current-period changes in exposures with days past due or exposures subject to forbearance measures are positively and statistically significantly related to ACL_t for stage 2, consistent with supervisory expectations of 30-days-past-due and forbearance measures serving as backstop indicators for SICR (European Banking Authority, 2017, pp. 41–42, 47–78).

Furthermore, changes in non-performing exposures (ΔNPE) are statistically significantly associated with Stage 2 and Stage 3 ACL_t. Specifically, positive

[11] Economic significance is calculated by multiplying the coefficient estimate by the in-sample standard deviation of the independent variable and dividing the result by the in-sample standard deviation of the dependent variable. This approach follows the method used by Novotny-Farkas et al. (2024, p. 16), allowing the interpretation of economic effects in units of the dependent variable's standard deviation.

relationships are observed for the current and subsequent period changes, whereas negative relationships emerge for the lagged ($t-1$) versions of the variables. The positive associations between changes in non-performing exposures and Stage 2 allowances suggest that banks may be delaying the recognition of losses. This pattern provides support for Hypothesis H_3, which posits that changes in non-performing exposures are positively associated with banks' provisioning for stage 2 and 3 exposures.

Interestingly, the relationship between changes in non-performing exposures and the overall impairment ratio (%Imp$_t$) is statistically significant but negative. As discussed by Novotny-Farkas et al. (2024, p. 18), this finding reflects the asymmetric relationship between %Imp$_t$ and changes in non-performing exposures, and thus should not be interpreted directly as a measure of provisioning timeliness[12].

The coefficient of GDPGrowth$_t$ is statistically significant and negative with %Imp$_t$ as well as Stage 2 and Stage 3 ACL$_t$, providing support for Hypothesis H_4. Moreover, the economic significance of the relationship between GDPGrowth$_t$ and Stage 2 and 3 ACL$_t$ is notable, with an estimated effect of -10.95 %.

Additional evidence supporting Hypothesis H_4 is provided by the negative relationships observed between the composite confidence indicator (CBC$_t$) and both the overall impairment ratio (%Impt$_t$) and Stage 2 and Stage 3 allowances (ACL$_t$). Again, the economic significance of these relationships is significant, with an estimated effect size of -18.64 %. Similarly, although the economic uncertainty variable (Δ%WUI$_t$) exhibits statistically significant relationships with provisioning measures, the associated economic significance is rather limited, at approximately -1.95 %. These findings provide evidence consistent with Hypothesis H_4.

[12] For further discussion regarding the measurement of timeliness in determinant models, see Section 4.2.7.

In contrast to the negative relationships observed for variables proxying the current macroeconomic environment, the relationships between forward-looking GDP growth forecasts ($GDPForGrowth_{t+1\text{-}4}$) and provisioning measures are positive and statistically significant for both the overall impairment ratio ($\%Impt_t$) and Stage 2 allowances ($ACLS2_t$). The economic significance with prior is 9.89 % While Hypothesis H_4 anticipates negative relationships for macroeconomic indicators, these results suggest that banks tend to increase provisioning when weaker future GDP growth is anticipated, which is consistent with counter-cyclical provisioning behaviour. Accordingly, in the case of forward-looking GDP forecasts, the results provide no evidence against the null hypothesis of no negative association.

Overall, the results posit that the negative relationship between the contemporaneous macroeconomic variable and ($\%Impt_t$) is stronger than the positive relationship between the forward-looking factor ($\%Impt_t$), providing further evidence of pro-cyclical provisioning behaviour.

Finally, the model diagnostics reported in Table 7 support the overall reliability of the regression results, though notable differences in explanatory power are observed across specifications. The model for Stage 3 allowances ($\Delta ACLS3_t$) shows very strong explanatory power, with an adjusted R^2 of 0.801, while the model for the overall impairment ratio ($\%Impt_t$) exhibits moderate explanatory power, with an adjusted R^2 of 0.290. By contrast, the models for Stage 1 and Stage 2 allowances ($\Delta ACLS1_t$ and $\Delta ACLS2_t$) have much lower adjusted R^2 values at 0.065 and 0.116, respectively. This suggests that a substantial portion of the variation in these early-stage allowances is not captured by the model, indicating greater heterogeneity in banks' Stage 1 and Stage 2 ECL practices and lower comparability across institutions. Overall, while the diagnostics reinforce confidence in the validity of the results for the overall impairment ratio and Stage 3 allowances, findings for early-stage allowances should be interpreted with greater caution.

4.4.2 Comparison with Prior Research

This chapter examines how the empirical results compare to findings from prior studies on the determinants of impairment provisioning. The analysis benchmarks the results against Novotny-Farkas et al. (2024). The purpose is to evaluate whether the key empirical relationships identified in their earlier work, continue to hold when tested over an extended period and under different macroeconomic conditions.

The results for earnings smoothing (Hypothesis H_1) broadly support the findings of Novotny-Farkas et al. (2024), confirming that banks continue to engage in income smoothing through impairment provisioning. In this study, the coefficient on $\%EBImpt_t$ is positive and highly statistically significant when explaining both the overall impairment ratio ($\%Impt_t$) and Stage 2 allowances ($\Delta ACLS2_t$), indicating stronger evidence compared to the more moderately significant relationship reported by Novotny-Farkas et al. (2024). While the economic significance of the smoothing effect remains very similar across the two studies (11.5% in this study versus 11.7% in Novotny- Farkas et al. (2024)), the stronger statistical significance provides additional support for the persistence of income smoothing behaviour under IFRS 9. Interestingly, whereas Novotny-Farkas et al. (2024) found the strongest smoothing effect at Stage 1, this study identifies a more pronounced relationship at Stage 2, suggesting a potential shift toward smoothing behaviour associated with riskier exposures.

In contrast, the evidence for capital management behaviour (Hypothesis H_2) is notably weaker in this study. The coefficient on the capital management proxy (LOW $CET1_{t-1}$) is statistically insignificant across all model specifications, whereas Novotny-Farkas et al. (2024) reported a significant association with Stage 2 allowances. However, the original evidence was already somewhat limited: Novotny-Farkas et al. (2024) did not find a statistically significant relationship for LOW $CET1_{t-1}$ when their sample was split into COVID-19 and non-COVID-19 periods, suggesting that the earlier finding may have been sensitive to specific sample conditions rather than indicative of a stable behavioural pattern. Moreover, as discussed in Chapter 4.5.1, LOW $CET1_{t-1}$ is a quartile-based dummy variable, and minor differences in sample composition can affect group classifications and, consequently, the estimated relationships. Taken together, the results of this study suggest that while capital management incentives may still exist, they are not systematically reflected in provisioning behaviour over the extended observation period.

Regarding the timeliness of credit risk recognition (Hypothesis H_3), the results continue to show that increases in non-performing exposures (ΔNPE_t) are positively associated with higher provisioning for Stage 2 and Stage 3 loans, consistent with delayed loss recognition behaviour documented by Novotny-Farkas et al. (2024). Compared to the earlier study, the relationships found here are even more statistically robust, particularly for Stage 2 allowances. As in Novotny-Farkas et al. (2024), the association between ΔNPE_t and the overall impairment ratio ($\%Impt_t$) remains statistically significant but negative, which they find to reflect the asymmetric impact of non-performing loans on total provisions. Additionally, the lagged change in non-performing exposures (ΔNPE_{t-1}) exhibits a negative coefficient for Stage 2 allowances, suggesting that delayed credit deterioration may initially reduce provisioning needs before leading to subsequent increases. Overall, the findings confirm that the gradual adjustment of provisions in response to deteriorating credit quality persists under the extended sample period.

The findings related to macroeconomic indicators (Hypothesis H_4) broadly confirm the patterns observed by Novotny-Farkas et al. (2024). The negative association between contemporaneous GDP growth and provisioning measures persists, and also its economic significance (approximately -10.95%), is similar to earlier results. Similarly, forward-looking GDP forecasts ($GDPForGrowth_{t+1\text{-}4}$) continue to exhibit a positive and statistically significant association with provisioning, with an economic significance of approximately 9.89%. Although Novotny-Farkas et al. (2024) did not draw specific conclusions regarding GDP forecasts, their estimates indicate a comparable economic relevance (approximately −13.6% for GDP growth and 14.2% for GDP forecasts).

Additional macroeconomic indicators yield broadly consistent results. The economic sentiment proxy (CBC_t) shows a highly significant negative association with overall impairment and stage 1 and stage 2 allowances, mirroring the negative relationship found for the CLI index by Novotny- Farkas et al. (2024), but with greater statistical significance. Importantly, the economic significance of CBC_t is considerable (approximately −18.64%), contributing meaningfully to the overall macroeconomic impact. Similarly, the economic uncertainty proxy ($\Delta\%WUI_t$) exhibits a negative and statistically significant association with Stage 2 allowances, consistent with a procyclical provisioning pattern as observed in earlier studies.

Overall, these results reinforce the view that macroeconomic conditions continue to influence provisioning behaviour in a procyclical manner under IFRS 9, validating the conclusions drawn by Novotny-Farkas et al. (2024) even over the extended observation period.

In summary, the results of this study largely validate the findings of Novotny-Farkas et al. (2024) when tested on a broader and more recent dataset. Consistent with Hypothesis H_1, income smoothing behaviour persists, with a positive and statistically significant association between earnings before impairments and loan loss provisioning. In contrast to Hypothesis H_2, no evidence of capital management behaviour is found, as the capital adequacy proxy loses its statistical significance across all model specifications. In line with Hypothesis H_3, the results reaffirm delayed credit risk recognition, with changes in non-performing exposures positively associated with provisioning activity. Supporting Hypothesis H_4, macroeconomic conditions continue to exert a significant procyclical influence on provisioning, with indicators such as GDP growth and economic sentiment maintaining consistent effects. Overall, the findings confirm that discretionary provisioning behaviour under IFRS 9 persists across different macroeconomic environments, supporting the robustness of earlier empirical conclusions.

5 Conclusions

This study set out to examine banks' loan loss provisioning behaviour under the IFRS 9 ECL framework, with a particular focus on whether the patterns documented by Novotny-Farkas et al. (2024) persist over a longer and more recent observation period. Using publicly available data on European banks from the fourth quarter of 2018 through the second quarter of 2024, the study analysed the extent to which income smoothing, capital management, delayed loss recognition, and pro-cyclical provisioning continue to characterize banks' impairment practices.

The empirical results provide answers to all four research questions and largely confirm earlier findings. Specifically, the analysis shows that banks continue to use discretion in provisioning to manage reported income (RQ1). The evidence for capital management behaviour (RQ2) is notably weaker in this study as the capital management proxy does not show a statistically significant association with provisioning across model specifications, unlike in prior studies. Furthermore, the study finds continued evidence of delayed loss recognition (RQ3), indicating that banks may still postpone the timely recognition of credit losses, contrary to the objectives of the ECL framework. Finally, provisioning behaviour remains pro-cyclical despite the framework's forward-looking design (RQ4).

The findings have important implications for policy and practice. They underscore the need for continued supervisory attention to the use of discretion in impairment provisioning and highlight the importance of improving transparency in reported credit risk measures. Crucially, establishing a cross-industry consensus on provisioning methods would be an important step toward enhancing both transparency and comparability, which are essential not only for supervisors but also for investors and other market participants.

The persistent evidence of earnings management presents a mixed picture. While it may help smooth results and thus reduce banking sector procyclicality, it also functions as a judgment-based mechanism that can compromise the comparability of banks' reported provisions. Encouragingly, this study did not find evidence of capital management behaviour, which is a positive signal from a prudential perspective. It suggests that weakly capitalized banks are not systematically under-provisioning compared to their peers, thereby avoiding further weakening their capital positions as expected credit losses eventually materialize. This can be considered as reassuring both for their solvency and for financial stability more broadly.

At the same time, the study finds further evidence of delayed loss recognition, raising concerns that banks may still be forced to absorb losses into capital when risks materialize. Given that the IFRS 9 ECL framework was designed to promote more timely provisioning, these results suggest it has not yet fully achieved that aim. Finally, the study reinforces earlier findings of pro-cyclical provisioning behaviour, which carries the negative prudential implication that loan loss provisions continue to amplify cyclical fluctuations in bank capital and lending.

While this study provides updated evidence on IFRS 9 provisioning behaviour over a more recent and extended period, several limitations should be acknowledged. Although the sample covers a window that includes notable macro-financial developments, it may still fall short of capturing the full effects of distinct macroeconomic regimes, particularly those associated with more conventional recessionary conditions. Moreover, the analysis does not explicitly distinguish the pandemic period, which may limit the ability to observe potential temporal variation in provisioning responses. The study also faces limitations related to data granularity and measurement, which constrain the analysis of bank-level dynamics and time-varying effects. In addition, the focus on European banks limits the generalizability of the findings to other regions. These limitations point to valuable opportunities for future research using more detailed datasets and advanced panel methods to deepen understanding of the long-term effects of the ECL framework.

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Appendices

Appendix 1. Descriptive Statistics for LGD Parameter

Table 8. Descriptive Statistics for LGD.

Reg.	Portfolio	N	Mean	SD	P25	Median	P75	Min	Max
Europe	Corp.	31	39.4%	2.8%	38.1%	39.8%	40.8%	29.3%	44.5%
Europe	Corp. (SME)	31	36.9%	5.4%	34.8%	37.6%	40.2%	23.4%	44.1%
Europe	Corp. (SL)	31	27.3%	7.4%	22.4%	27.0%	28.8%	13.7%	45.0%
Europe	Retail	31	24.0%	3.0%	21.6%	23.9%	25.2%	20.2%	34.0%
Europe	Retail (Other)	31	41.8%	4.3%	38.5%	41.5%	43.7%	35.6%	51.1%
Europe	Retail (QL)	31	58.7%	2.3%	56.9%	58.2%	60.0%	54.9%	64.8%
Europe	Retail (SR)	31	17.6%	0.9%	17.0%	17.6%	18.0%	15.6%	20.7%
Other	Corp.	10	40.8%	3.4%	40.1%	40.7%	43.8%	33.7%	44.2%
Other	Corp. (SME)	10	38.1%	5.8%	36.0%	37.6%	43.1%	26.9%	45.0%
Other	Corp. (SL)	10	25.7%	7.9%	19.5%	26.6%	28.4%	15.4%	40.7%
Other	Retail	10	20.4%	2.1%	18.3%	20.6%	21.5%	17.7%	23.8%
Other	Retail (Other)	10	37.9%	3.6%	35.5%	36.9%	40.5%	33.0%	43.4%
Other	Retail (QL)	10	58.7%	1.5%	57.9%	59.1%	59.7%	56.4%	60.5%
Other	Retail (SR)	10	17.4%	0.8%	17.0%	17.3%	17.6%	16.6%	19.2%

Note. SL = Spec. Lending, QL = Qual. Revolving & SR = Sec. Real Estate

Appendix 2. Descriptive Statistics for PD Parameter

Table 9. Descriptive Statistics for PD.

Reg.	Portfolio	N	Mean	SD	P25	Median	P75	Min	Max
Europe	Corp.	31	0.8%	0.3%	0.6%	0.8%	1.0%	0.4%	1.9%
Europe	Corp. (SME)	31	1.9%	0.8%	1.3%	1.8%	2.2%	1.0%	4.2%
Europe	Corp. (SL)	31	1.0%	0.7%	0.6%	0.8%	1.0%	0.4%	4.0%
Europe	Retail	31	1.3%	0.2%	1.1%	1.3%	1.4%	0.9%	1.9%
Europe	Retail - Other	31	2.4%	0.6%	2.0%	2.5%	2.8%	1.3%	3.4%
Europe	Retail (QL)	31	1.4%	0.5%	1.0%	1.3%	1.5%	0.8%	3.4%
Europe	Retail (SR)	31	0.8%	0.3%	0.6%	0.8%	1.0%	0.2%	1.3%
Other	Corp.	10	3.7%	8.7%	0.5%	0.7%	0.8%	0.4%	28.4%
Other	Corp. (SME)	10	4.3%	6.0%	0.8%	1.7%	3.8%	0.6%	18.5%
Other	Corp. (SL)	10	3.5%	7.6%	0.6%	0.8%	1.5%	0.4%	25.0%
Other	Retail	10	0.9%	0.2%	0.7%	0.9%	1.1%	0.5%	1.2%
Other	Retail Other	10	1.9%	0.8%	1.2%	1.8%	2.1%	0.9%	3.2%
Other	Retail (QL)	10	0.9%	0.4%	0.5%	0.9%	1.2%	0.4%	1.5%
Other	Retail (SR)	10	0.8%	0.4%	0.6%	0.8%	0.9%	0.3%	1.7%

Note. SL = Spec. Lending, QL = Qual. Revolving & SR = Sec. Real Estate

Appendix 3. Disclosure of AI Assistance

In preparing this thesis, I made use of generative artificial intelligence (AI) tools, namely ChatGPT, to support both the coding work conducted in R and the writing process. AI tools were employed to help draft text, refine wording and improve the overall clarity and coherence of the thesis. All decisions concerning the selection of literature, the conduct of analyses, the interpretation of results, and the final formulation of the text were made independently by me.