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Sectoral Credit Allocation and Bank Performance: The Impact of Exposure to Real Estate and Construction in Portuguese Banks

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SECTORAL CREDIT ALLOCATION AND BANK PERFORMANCE: THE IMPACT OF EXPOSURE TO REAL ESTATE AND CONSTRUCTION IN PORTUGUESE BANKS

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This dissertation marks the end of a demanding academic journey, but at the same time very enriching. It was not always an easy path, but without a doubt, it was an experience of growth, resilience and learning that I will carry with me throughout my life.

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Abstract

This dissertation analyses the relationship between the sectoral allocation of loan portfolios and the profitability of Portuguese banks for the period 2009 to 2023, focusing on exposures to the real estate and construction sectors.

We estimated the impact on banks' profitability (ROA, ROE and NIM) using dynamic fixed-effects models with panel data (bank-year) compiled by the Banco de Portugal (BPLIM).

We find a positive relationship between exposure to the real estate and construction sectors and profitability. The results are stronger for ROA and ROE measures. However, there is no statistically significant evidence that sectoral concentration of credit portfolios affects bank profitability. We analyse these relationships over different financial crises, and the results suggest that the impact varies depending on the economic and financial context.

Overall, the results show that the profitability of Portuguese banks over the last 15 years was affected by the sectors to which credit is granted but not by the degree of concentration of credit portfolios.

Keywords: Bank Profitability; Credit Portfolio Composition; Exposures to Real Estate and Construction; Bank Lending; Portugal; Banking and Financial Crises

JEL Codes: G21, G32, E32, R31

Resumo

A presente dissertação analisa a relação entre a alocação setorial das carteiras de crédito e a rentabilidade dos bancos portugueses para o período de 2009 a 2023, com foco nas exposições ao setor imobiliário e da construção.

Estimamos o impacto na rentabilidade dos bancos (ROA, ROE e NIM) através de modelos dinâmicos de efeitos fixos com dados em painel (banco-ano) compilados pelo Banco de Portugal (BPLIM).

Os resultados sugerem uma relação positiva entre a exposição do crédito concedido aos setores imobiliário e da construção e a rentabilidade. Os resultados são mais expressivos para as medidas de ROA e ROE. Contudo, não há evidência estatística significativa de que a concentração setorial das carteiras de crédito afete a rentabilidade bancária. Quando analisamos estas relações durante as diferentes crises financeiras, verificamos que o impacto varia com o contexto económico e financeiro.

Em suma, os resultados obtidos mostram que a rentabilidade dos bancos portugueses nos últimos 15 anos é influenciada pelos setores aos quais o crédito é concedido, mas não do grau de concentração das carteiras de crédito.

Palavras-chave: Rentabilidade Bancária; Composição da Carteira de Crédito; Exposições ao Setor Imobiliário e Construção; Empréstimos Bancários; Portugal; Crises Bancárias e Financeiras.

Códigos JEL: G21, G32, E32, R31

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List of Acronyms

BPLIM. Banco de Portugal Microdata Research Laboratory

ECB. European Central Bank

FE. Fixed Effects

GDP. Gross Domestic Product

GFC. Global Financial Crisis

HCRC. Historical Central Credit Register

HHI. Herfindahl-Hirschman Index

LTV. Loan-to-value

NIM. Net Interest Margin

POLS. Pooled Ordinary Least Squares

RE. Random Effects

RECExposure. Real Estate and Construction Credit Exposure

ROA. Return on Assets

ROE. Return on Equity

SLB. Historical Series of the Portuguese Banking Sector

VIF. Variance Inflation Factors

1. Introduction

The banking system plays a pivotal role in the functioning of the modern economy, with a central role in financial intermediation, the mobilisation of savings and the financing of economic activity. This is of particular importance in bank-based economies, where the banking sector is the main channel for financing households and businesses. The soundness and performance of these institutions are key factors for economic growth and the efficient functioning of financial markets. Sectoral allocation of banks' loan portfolios may influence banking profitability and risks and therefore the stability of the financial system. Several studies have extensively examined the impact of loan sector allocation on the profitability of banks and financial stability over time, in the different phases of economic and financial cycles.

When considering exposure to the various economic sectors, the real estate and construction sector occupies a particularly significant position due to its strong links with the banking system and relevance in banks' balance sheets. Historically, episodes of credit expansion to the real estate and construction sectors are often associated with periods of rapid economic growth, but also with subsequent increased vulnerability of banks. According to the literature, property credit tends to exacerbate economic cycles, particularly due to the role of property assets as collateral and the sector's high sensitivity to the surrounding macroeconomic environment (Kiyotaki & Moore, 1997; Schularick & Taylor, 2012). Thus, excessive exposure to these sectors can increase the vulnerability of banks to potential adverse shocks, which reinforces the importance of analysing the relationship between the sectoral composition of loan portfolios and bank profitability over time.

While there is a vast body of literature on the determinants of bank profitability, the empirical evidence focusing on the sectoral composition of loan portfolios is scarce, particularly for specific economies such as Portugal. Most studies focus on traditional factors, such as capitalisation, size, operational efficiency or credit risk, while sectoral exposure is often analysed only in aggregate terms or from a financial stability perspective. Furthermore, the relationship between credit portfolio concentration, exposure to the real estate and construction sectors, and banking performance remains inconclusive in the literature, particularly during periods of financial instability and severely adverse macroeconomic conditions.

Financing granted to the real estate and construction sectors has specific characteristics that make it particularly relevant for assessing banking performance. Lending to firms operating in the real estate and construction sectors tends to benefit from the use of real assets as collateral. This leads to a lower perception of risk during periods of economic growth, given the dependence on the quality of these assets on the evolution of property prices.

In this context, several studies show that greater exposures to the real estate and construction sectors tends to amplify economic and financial cycles, particularly because property assets are used as collateral. During periods of economic growth, rising property values tend to stimulate credit expansion, leading to a consequent increase in banks' exposure to the real estate and construction sectors. Yet during periods of economic contraction, these exposures lead to a rapid deterioration in asset quality and a reduction in bank profitability (Allen & Gale, 2000; Jordà et al., 2013).

Related literature focuses on the impact of concentration and diversification of credit portfolios. The degree of sectoral concentration can influence banks' performance in various ways and the relationship between portfolio concentration and bank profitability is ambiguous in the empirical literature. Some studies show that greater diversification helps to reduce the risk associated with sector-specific shocks. On the other hand, other authors argue that specialisation strategies may lead to increased profitability through efficiency gains, greater customer knowledge and competitive advantages in certain market segments (Acharya et al., 2006; Tabak et al., 2011).

The issues outlined above are particularly relevant to the Portuguese context, given that, in recent decades, the banking system has maintained significant exposure to the real estate and construction sectors. At the same time, the Portuguese economy has been heavily affected by several periods of financial instability, notably the global financial crisis of 2008, the European sovereign debt crisis and, more recently, the economic effects associated with the COVID-19 pandemic (Banco de Portugal, 2021; Castro, 2013). While it is well established that these episodes weakened the financial conditions of many banks, there is room for further research to estimate these effects across banks with different sectoral credit allocations (Acharya et al., 2006; Koetter & Poghosyan, 2010; Schularick & Taylor, 2012).

This dissertation assesses the relationship between the sectoral allocation of loan portfolios and the profitability of Portuguese banks over the period from 2009 to 2023. The first goal

of this study focuses on the exposures to the real estate and construction sectors. Moreover, we assess whether and how the degree of sectoral concentration in credit portfolios influences the performance of Portuguese banking institutions. We evaluate whether this relationship varies throughout the economic and financial cycles.

The empirical analysis uses bank-year panel data provided by *Banco de Portugal* (BPLIM). We estimate a dynamic and fixed-effects model with robust clustered errors at the bank level, to evaluate the role of sectoral exposure and loan portfolio concentration on bank profitability, proxied by Return on Assets (ROA), Return on Equity (ROE) and Net Interest Margin (NIM).

This study contributes to the literature in several ways. First, it provides up-to-date empirical evidence on the profitability of the Portuguese banking system and its determinants over an extended time horizon. Second, we provide evidence on how exposures to the real estate and construction sectors impact profitability over time and across the several financial cycles analysed.

This dissertation is structured as follows. Chapter 2 presents a review of the literature on the determinants of bank profitability, as well as the sectoral composition of credit, real estate and construction exposures, portfolio concentration and economic cycles. Chapter 3 sets out the research questions and empirical hypotheses of this study. Chapter 4 presents the methodology adopted, the econometric models, the data and descriptive statistics. Chapter 5 presents the empirical results and discusses the main findings. Finally, Chapter 6 sets out the main conclusions of the research, as well as the limitations and possible suggestions for future research.

2. Literature Review

Bank profitability across institutions and over time has been widely studied in the banking literature and is explained by bank characteristics, as well as macroeconomic and structural conditions of the financial system. Some recent studies suggest that the way banks allocate credit across sectors helps explain their performance. The sectoral composition of loan portfolios seems to affect both banks' profitability and risk, especially in the case of exposures to more cyclical sectors, such as real estate and construction.

In this dissertation, real estate and construction exposure refers to the credit granted to non-financial corporations operating in the construction and real estate sectors, excluding household mortgage lending. This distinction is important because the analysis focuses on banks' exposure to corporate sector activities rather than on lending to households.

Since factors such as credit cycles, financial crises and macroprudential policies affect the performance of financial institutions over time and affect some sectoral exposures more severely, the relationship needs to be assessed in a dynamic way.

In this chapter, we review the major studies that analyse the determinants of bank profitability, in particular the allocation and composition of loan portfolios, and exposures to the real estate and construction sectors.

2.1. Sectoral Allocation of Loan Portfolios

The banking literature highlights the importance of sectoral allocation of loan portfolios on the financial performance of banks and their exposure to risk in the different phases of the economic cycle.

Each economic sector presents different characteristics in terms of risk, return, financing needs, sensitivity to economic cycles and the availability of collateral assets. These differences may lead banks to adopt distinct lending strategies across sectors (Diamond, 1984; Gehrig, 1998; Wurgler, 2000).

Empirical evidence shows that the sectoral allocation of loan portfolios influences banking performance. In particular, greater exposure to higher-risk sectors may negatively affect banking performance and increase vulnerability to adverse shocks. Consequently, the composition of loan portfolios is not only a structural feature of banks, but also helps to

explain differences in financial performance across institutions (Andrieş et al., 2025; Berger et al., 2010; Tabak et al., 2011).

Banks' lending strategies are linked to the allocation of credit across different economic sectors and to the investment opportunities available in the economy. The empirical literature shows that some sectors tend to receive a higher proportion of bank credit, particularly when they can be used as collateral and are associated with lower levels of risk. Thus, banks' decisions regarding the allocation of credit across sectors tend to be influenced by credit demand, as well as by concerns relating to profitability and risk management (Azevedo et al., 2022; Gan, 2007; Rajan & Winton, 1995).

Decisions related to credit allocation are also influenced by the regulations in force and the institutional framework. In particular, macroprudential measures, capital requirements and changes in monetary policy conditions can influence banks' lending behaviour and lead to adjustments in the composition of their loan portfolios (Borio et al., 2017; Dell'Ariccia et al., 2016).

According to reports published by the European Central Bank (ECB), periods of low interest rates and favourable financing conditions can stimulate credit expansion, particularly in sectors closely linked to real estate and construction. However, tighter monetary policy conditions and stricter prudential requirements can help reduce exposure to higher-risk credit and encourage banks to rebalance their loan portfolios (European Central Bank, 2017, 2022a, 2025).

In addition, macroprudential instruments, such as countercyclical capital buffers, loan-to-value (LTV) limits and borrower-based measures, have been increasingly used to mitigate excessive credit growth and reduce vulnerabilities associated with highly concentrated sectoral exposures. These measures have become relevant in the wake of the global financial crisis, given the strong link between credit expansion, property markets and financial instability (European Central Bank, 2024b).

There is also evidence that the sectoral allocation of credit tends to be pro-cyclical throughout economic cycles. During periods of economic expansion, banks tend to increase their exposure to sectors associated with higher profitability and asset valuations, leading to a greater concentration of credit in certain segments of the economy. This behaviour is associated with stronger credit demand, improved economic expectations and a lower

perception of risk during periods of economic growth. However, this mechanism may increase the vulnerability of banks, particularly when they maintain significant exposure to sectors that are highly sensitive to the economic cycle (Kiyotaki & Moore, 1997; Minsky, 1986).

Another major factor related to the sectoral allocation of credit is credit risk. The composition of the loan portfolio has a direct influence on banks' exposure to credit risk, since economic sectors differ financially and exhibit varying degrees of sensitivity to macroeconomic conditions. As a result, banks may face different levels of default risk, depending on their sectoral exposures. Empirical results show that adverse macroeconomic developments, such as a slowdown in economic activity and falling asset prices, can weaken borrowers' repayment capacity and contribute to a deterioration in credit quality (Louzis et al., 2012; Nkusu, 2011).

When there is an increase in credit risk, adverse effects on banks' performance may arise through impairments and loan-loss provisions. High levels of defaults tend to reduce the net income on credit activity and require banks to set aside additional provisions for potential losses. Thus, sectoral exposures associated with higher credit risk may negatively affect banks' profitability and overall financial performance (Bolt et al., 2012; Chakraborty & Dekle, 2009).

The distribution of credit across the various economic sectors is influenced by the different characteristics of each sector, particularly in terms of profitability, risk and financing needs. In this regard, banks do not distribute credit uniformly and tend to adjust their lending decisions in line with market conditions and strategic objectives. The literature shows that these decisions reflect the trade-off between risk and return, with possible implications for banking performance and financial stability (Bikker & Hu, 2002; Winton, 2000).

Information asymmetries tend to influence credit decisions, and banks seek to direct credit towards sectors where they have a greater informational advantage. Consequently, this may improve the efficiency of the selection and monitoring processes. Sectoral allocation does not depend solely on return expectations, but also on the informational environment in which they operate, leading to a greater concentration in sectors where they have more experience (Diamond, 1984; Gehrig, 1998).

Finally, collateral also plays a crucial role in mitigating information asymmetries, as well as aligning incentives between lenders and borrowers. In this sense, sectors with a greater availability of assets that can be used as collateral tend to attract a higher share of bank credit, as collateral reduces the perception of risk associated with lending activities (Chaney et al., 2012; Rajan & Winton, 1995).

Taken together, the literature reveals that the sectoral composition of credit is not neutral, but rather reflects strategic decisions by banks that may influence risk, profitability and the allocation of financial resources. Differences in the distribution of credit across economic sectors may result in different levels of portfolio concentration. This phenomenon has been widely explored in the literature through the debate between diversification and specialisation strategies, as well as their implications for banking performance. This is a particularly relevant topic for the present research and is discussed in the following section.

2.2. Sectoral Diversification and Concentration in Credit Portfolios

The debate between sectoral diversification and concentration strategies has received considerable attention in the banking literature. Since the distribution of credit across sectors may result in different levels of portfolio concentration, researchers have examined whether banks benefit more from spreading their exposures across a wide range of activities or from specialising in a smaller number of sectors. The implications of these strategies for risk, profitability and financial stability remain a central issue in the literature.

According to the classical literature, bank diversification reduces risk by limiting exposure to sector-specific shocks. Through the allocation of credit across different economic activities, idiosyncratic risks are mitigated and the volatility of financial performance is reduced. In this sense, negative shocks in one sector can be offset by more favourable outcomes in others, which increases the resilience of credit portfolios (Diamond, 1984; Tabak et al., 2011).

However, empirical evidence suggests that the relationship between diversification and banking performance is not always straightforward. Acharya, Hasan and Saunders (2006) argue that greater specialisation, combined with effective monitoring, may lead to better results than excessive diversification. The authors show that diversification may reduce profitability when banks expand their activities into sectors in which they do not possess

sufficient knowledge or expertise. These effects may arise because diversification increases monitoring and information costs when banks expand into unfamiliar sectors.

In line with this perspective, concentration may enable banks to build stronger relationships with borrowers operating in specific sectors, thereby improving information advantages and reducing screening costs. Banks with greater sectoral specialisation tend to develop a deeper understanding of the characteristics and risks associated with certain economic activities, which may improve lending decisions and contribute to higher profitability. Consequently, the relationship between concentration and banking performance is not necessarily negative. Rather, it depends on the institutional capacity to manage the specific risks associated with each sector (Acharya et al., 2006; Gehrig, 1998; Rajan & Winton, 1995).

Later, Berger, Hasan, and Zhou (2010) analysed the effects of diversification in Chinese banks between 1996 and 2006 using several measures of diversification, including loans, deposits and geographic presence. Their results suggest that higher levels of diversification are associated with lower profitability and higher operating costs. The authors argue that more focused strategies may lead to better performance, as specialised institutions are often better positioned to control costs and allocate resources more efficiently.

Banks with higher levels of capitalisation tend to face a lower risk of insolvency, as they are better equipped to absorb adverse financial shocks. Furthermore, greater portfolio concentration is associated with higher profitability without a proportional increase in insolvency risk. These findings suggest that concentration is not necessarily detrimental to banking performance and that its effects may vary according to the characteristics of each institution. Consequently, the relationship between concentration, risk and profitability appears to be more complex than traditionally assumed (Bourke, 1989; Tabak et al., 2011).

The literature suggests that neither diversification nor concentration is universally superior. While diversification may reduce risk through greater portfolio diversification, concentration can generate efficiency and profitability gains under certain conditions. Consequently, the relationship between concentration, risk and performance appears to be non-linear, depending on factors such as the macroeconomic environment and the characteristics of individual institutions (Cerasi & Daltung, 2000; Winton, 2000).

The analysis of diversification in credit portfolios is often based on indicators such as the Herfindahl-Hirschman Index (HHI)[1], which measures the level of concentration of banks' exposure to certain economic sectors. The use of the HHI is particularly relevant in the banking context, as it provides a measure of the dependence of institutions on specific economic segments. Higher HHI values indicate a greater reliance on a limited number of sectors, whereas lower values reflect more diversified credit allocation strategies (Hirschman, 1945). Thus, the introduction of concentration indicators such as the HHI makes it possible to capture the structure of portfolios in a single measure, making it an important tool for the empirical analysis of how the sectoral composition influences bank performance (Stiroh, 2004).

The implications of portfolio concentration become particularly evident during periods of economic expansion and downturn. During expansionary phases, banks may increase their exposure to sectors perceived as more profitable, leading to higher levels of concentration in specific market segments. However, when economic conditions deteriorate, negative shocks affecting those sectors may have disproportionate effects on banks' asset quality and financial performance. These dynamics highlight the importance of understanding how sectoral concentration shapes banks' vulnerability to changing economic conditions (Abbas et al., 2025; Dell'Ariccia et al., 2016).

For the present study, the analysis of sectoral credit allocation is particularly relevant, as it provides a framework for understanding how exposure to specific economic sectors may influence banking performance, especially in the case of construction and real estate activities. The literature on sectoral diversification and concentration is also important for the development of the empirical model, particularly through the use of the Herfindahl-Hirschman Index (HHI), which captures the degree of concentration of credit portfolios and allows an assessment of its implications for bank profitability. This discussion provides the foundation for the following section, which focuses on the exposure to the construction and real estate sectors, the central theme of this research.

[1] The Herfindahl-Hirschman Index (HHI) is frequently used by various authors to measure levels of concentration and is calculated as the sum of the squares of the sectoral shares of credit exposure.

2.3. Real Estate and Construction Exposures and Bank Performance

Among the various sectors that receive bank credit, real estate and construction activities have attracted particular attention in the banking literature. These sectors play a central role in credit markets due to their strong links with collateral values, investment activity and financial cycles. As a result, banks' exposure to real estate and construction activities may have important implications for profitability, risk and overall financial stability.

It is important to emphasise that this study does not focus on mortgage loans granted to households, but rather on banks' exposure to real estate and construction activities through lending to non-financial corporations. The relevance of these sectors stems largely from the characteristics of the assets underlying the loans. Credit granted to firms operating in real estate and construction activities is often backed by collateral, which may reduce perceived risk and encourage lending during periods of economic stability. However, these benefits depend heavily on the evolution of asset values, making banks particularly vulnerable when property prices decline (Gan, 2007; Iacoviello, 2005). Moreover, this also applies to real estate exposure through households' mortgage lending collateral.

Real estate and construction are considered cyclical sectors, which makes banks more exposed to economic vulnerabilities and shocks when these sectors represent a large share of their credit portfolios (Albertazzi & Gambacorta, 2009; Goddard et al., 2004). Thus, exposure to real estate and construction activities should be considered a central dimension of banking activity and one of the main channels through which profitability, risk and financial stability are linked (Carmichael & Coën, 2018; Gan, 2007; He et al., 1996).

Kiyotaki and Moore (1997) argue that asset values and indebtedness tend to rise as the value of collateral increases. This process makes it easier to obtain new financing and boosts investment. However, a fall in asset prices reduces collateral values and restricts access to credit. As a result, adverse shocks to asset prices may lead to credit contractions, which increase the likelihood of persistent effects on output and financial stability.

The attractiveness of real estate and construction activities for banks is closely related to the nature of the assets underlying the loans. Compared with other forms of corporate financing, lending to firms operating in these sectors is often supported by tangible assets that can be used as collateral, reducing the perceived level of ex ante risk. Shocks affecting real estate and construction markets influence firms' borrowing capacity through the collateral channel and, consequently, their investment decisions. In this sense, banks' exposure to real estate

and construction activities extends beyond housing credit, as the value of the assets held by firms directly affects their access to finance. As asset values increase, firms are able to expand their borrowing capacity and investment activity, whereas declines in asset values may constrain financing and investment (Bernanke & Gertler, 1995; Kiyotaki & Moore, 1997).

However, if there is a decline in property values, the process may reverse, leading to deterioration in the quality of banks' portfolios. Thus, the evolution of the real estate and construction markets has consequences for business financing, which affects the composition and performance of banking portfolios (Chaney et al., 2012; Liu et al., 2013).

The literature suggests that the performance of the banking sector is closely linked to developments in real estate markets. Institutions with greater exposure to real estate and construction activities tend to be more sensitive to fluctuations in asset prices and market conditions. This evidence suggests that changes in real estate markets may affect banks' profitability and risk exposure, underscoring the importance of understanding the composition of credit portfolios (Davis & Zhu, 2009; He et al., 1996).

At the European level, Martins et al. (2016) confirm that exposure to the real estate market has important implications for the banks' performance. According to the authors, real estate market risk is reflected in shareholder returns of banks in 15 European countries and represents a relevant source of systematic risk. This evidence suggests that the relationship between banks and real estate markets extends beyond the effects on credit quality observed ex post, influencing broader measures of performance and risk.

Beyond its effects on credit quality and profitability, real estate exposure may also influence the market valuation of banking institutions. Real estate risk constitutes a systematic factor in the determination of bank returns, remaining relevant even after controlling for traditional market and credit risk factors (Carmichael & Coën, 2018). At the same time, banks with greater exposure to real estate credit tend to be more sensitive to developments in real estate markets, reinforcing the importance of analysing the composition of credit portfolios when assessing banking performance (Davis & Zhu, 2009).

Moreover, the relationship between exposure to real estate and construction activities and banking performance is strongly influenced by the economic cycle and the evolution of asset values. Fluctuations in property prices are closely linked to banks' credit risk, as declines in asset values tend to deteriorate the quality of credit portfolios (Goodhart & Hofmann, 2008).

Banks with significant exposure to real estate and construction activities may become more vulnerable to adverse shocks. Furthermore, periods of rapid growth in property prices are often associated with a higher probability of systemic banking crises, suggesting that excessive exposure to these sectors may increase long-term financial vulnerabilities (Crowe et al., 2013). Deteriorating credit quality, declining collateral value and the correlation of exposures across financial institutions are the direct channels through which shocks are transmitted (Deng et al., 2019).

The importance of property markets extends beyond firms operating directly in the real estate and construction sectors. As real estate assets are often used as collateral for business financing, rising property values tend to increase firms' access to credit and stimulate investment (Lustig & Van Nieuwerburgh, 2005). The effects of developments in real estate and construction markets are transmitted beyond these sectors, including companies whose borrowing capacity depends on the value of the assets they hold (Liu et al., 2013). In this context, developments of real estate and construction markets can influence the composition and risk profile of banks' loan portfolios (Iacoviello, 2005).

Furthermore, exposure to real estate and construction activities may also affect banks' Net Interest Margin (NIM). Higher levels of risk associated with these sectors could increase banks' funding costs, as investors require greater compensation for risk. However, competitive pressures may limit banks' ability to transfer these costs to borrowers through higher lending rates. At the same time, a deterioration in asset quality may weaken banks' financial performance through higher credit losses and provisioning requirements. Consequently, greater exposure to real estate and construction activities may negatively affect banks' NIM, although these effects are likely to be temporary (Angelini & Cetorelli, 2003; Li et al., 2016).

In summary, the literature suggests that exposure to real estate and construction activities plays an important role in shaping banks' profitability, risk and financial stability. The evidence indicates that the effects of such exposure operate through several channels, including collateral values, firms' borrowing capacity, credit quality and funding conditions. However, the relationship is not straightforward, as its impact depends on the degree of exposure and on developments in real estate and construction markets. These findings highlight the importance of analysing the sectoral composition of credit portfolios in order

to better understand differences in banking performance and provide the foundation for the research questions developed in the following section.

3. Research Questions and Hypotheses

The literature reviewed in the previous chapter shows the importance of credit portfolio composition in shaping banks' performance and risk profiles. In particular, the allocation of credit across economic sectors may influence profitability, financial stability and vulnerability to adverse shocks. These findings provide the basis for examining how exposure to real estate and construction activities affects bank profitability. Previous studies typically assess banking profitability through measures such as ROA (Return on Assets), ROE (Return on Equity) and NIM (Net Interest Margin) (Athanasoglou et al., 2008; Goddard et al., 2004; Molyneux & Thornton, 1992).

Empirical evidence further suggests that the distribution of credit by different economic sectors reflects structural differences in risk, return and financing needs across banks (Beck & Levine, 2002; Wurgler, 2000). The degree of concentration of credit portfolios, often analysed according to the Herfindahl-Hirschman Index (HHI), is also a crucial factor, and can play an important role in explaining bank profitability (Acharya et al., 2006; Hirschman, 1945).

Exposure to real estate and construction has received considerable attention in the literature due to its cyclical nature and strong relationship with collateral values. In addition, empirical evidence on financial cycles suggests that the relationship between credit and profitability is not static, there is variation over time as a function of macroeconomic conditions.

The review in the previous chapter shows there are still open questions and some controversy on the effects of sectoral composition and concentration/diversification strategies on bank profitability and performance. Our research questions were developed accordingly, focusing on profitability effects. There are:

RQ1: Does exposure to the real estate and construction sectors influence bank profitability?

H1: Exposure to the real estate and construction sectors has a significant impact on bank profitability. (The null hypothesis is *no impact*)

RQ2: Does a more concentrated or diversified sectoral credit portfolio affect bank profitability?

H2: The degree of sectoral credit portfolio concentration has a significant impact on bank profitability. (The null hypothesis is *no impact*)

RQ3: Does the relationship between exposure to the real estate and construction sectors and bank profitability vary throughout economic cycles and periods of crisis?

H3: The impact of exposure to the real estate and construction sectors on bank profitability varies across economic cycles and periods of crisis. (The null hypothesis is *the impact is time-invariant*.)

The research questions and hypotheses presented above provide the foundation for the empirical analysis. The following chapter describes the methodological approach and the empirical tests used to address these questions.

4. Methodology

In this chapter, we first present the econometric and empirical strategy models adopted in the analysis. Then we turn to the characterisation of the data and the sample and the definition of the dependent and explanatory variables. Finally, we present a set of exploratory analyses that highlight possible significant relationships related to the research questions.

4.1. Empirical Strategy

Our approach is consistent with the empirical studies reviewed in Chapter 2 on the determinants of bank profitability. In particular, we evaluate the role of the sectoral composition of loan portfolios in explaining differences in bank profitability and performance.

The research is conducted using a bank-year panel econometric model, making it possible to simultaneously address differences over time and across banks. This methodology is appropriate as it controls for unobservable characteristics that tend to affect banks' profitability (Baltagi, 2005; Imbierowicz & Rauch, 2014).

We use a dynamic model of bank profitability. In practice, bank profitability does not immediately reflect macroeconomic shocks or structural changes in the loan portfolios, as banks adjust gradually to new conditions. The inclusion of a lag term allows us to capture the gradual adjustment process, preventing the specification from becoming overly restrictive. This is a widely used strategy in the banking context, as the effects of sectoral composition extend over time (Athanasoglou et al., 2008; Goddard et al., 2004).

In addition, the empirical framework incorporates bank fixed effects and year fixed effects, allowing the analysis to control for unobserved bank-specific characteristics and common shocks that may affect all banks. Such factors include changes in monetary policy, interest rate conditions, regulatory reforms, business cycle fluctuations and major crisis episodes, which may influence banks' profitability.

The specification is based on the standard bank profitability literature, particularly Athanasoglou et al. (2008) and Goddard et al. (2004), but we adapt it to address the specific research question outlined above.

4.2. Model Specification

This section describes the econometric models used to analyse the relationship between the sectoral allocation of loan portfolios and bank profitability. The proposed specifications allow us to estimate i) the impact of exposure to the real estate and construction sector on banks' profitability; ii) the impact of the level of sectoral concentration of loan portfolios on banks' profitability; and iii) the time-varying impact of these relations over economic and financial cycles.

First, we estimate the baseline model using different measures of bank profitability. Following the literature (Pasiouras & Kosmidou, 2007; Trujillo-Ponce, 2013), profitability is assessed using these measures: ROA, ROE and NIM. Although all three indicators measure bank profitability, they capture different dimensions of profitability. ROA and ROE measure overall profitability and are influenced by factors such as impairment charges and changes in banks' capital positions. In contrast, NIM focuses on the profitability of financial intermediation, reflecting the spread between interest income and interest expenses. By looking at these complementary indicators, we can better assess whether the effects of sectoral credit allocation differ across alternative measures of bank profitability (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011; Petria et al., 2015).

In the second specification, crisis-period variables and interaction terms are introduced to examine whether the relationship between sectoral credit allocation and bank profitability changes during periods of economic and financial distress. The consideration of crisis periods is consistent with the literature on financial cycles, which shows that the impact of credit and sectoral exposure is not constant over time, but may vary according to macroeconomic and financial conditions (Jordà et al., 2013; Schularick & Taylor, 2012).

Below we describe the two specifications in detail.

4.2.1. Baseline Model Specification

The econometric specification of the base model is defined as follows:

$$Profitability_{i,t} = \alpha + \beta_1 Profitability_{i,t-1} + \beta_2 RECExposure_{i,t} + \beta_3 HHI_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad \textbf{(4.2.1.)}$$

This econometric specification allows us to test hypothesis H1 by examining whether sectoral allocation has a significant impact on bank profitability.

In this econometric model, the dependent variable $Profitability_{i,t}$ represents the three measures of bank profitability (ROA, ROE and NIM) for bank i at time t.

The use of the lagged dependent variable $Profitability_{i,t-1}$, allows us to capture the persistence of bank profitability over time, reflecting the gradual adjustment of bank performance to changes in economic and financial conditions (Athanasoglou et al., 2008; Goodhart & Hofmann, 2008).

The use of lagged factors helps to mitigate potential endogeneity issues, particularly the possibility of simultaneity between credit allocation decisions and bank performance. Since bank profitability is associated to macroeconomic conditions, it could impact credit allocation decisions. Using a time lag helps mitigate this potential endogeneity issue (Kiyotaki & Moore, 1997).

The variable $RECExposure_{i,t}$ represents the share of total corporate credit allocated to the real estate and construction sectors. It is calculated as the ratio between performing credit granted to firms operating in the real estate and construction sectors and total performing corporate credit. Higher values indicate greater bank exposure to the real estate and construction sectors.

The literature does not provide a clear prediction regarding the effect of $RECExposure$ on bank profitability. On the one hand, greater exposure to the real estate and construction sectors may increase profitability. On the other hand, it may also increase banks' vulnerability to sector-specific shocks and cyclical fluctuations. Therefore, the sign of the coefficient associated with this variable is ultimately an empirical matter. The significance of this parameter will inform RQ1.

$HHI_{i,t}$ measures the degree of concentration of credit across different sectors, using the Herfindahl-Hirschman Index. The HHI is computed as the sum of squared sectoral credit shares. The index is based on six economic sectors available in the BPLIM database. There are: agriculture, construction, industry, utilities, services and other activities. Mortgage and consumer credit are excluded from the calculation, because they correspond to household

lending segments rather than economic sectors. Higher values of HHI indicate greater concentration in sectoral credit allocation. Given the presence of occasional negative values within the residual "other activities" category, absolute values were used when constructing sectoral shares to ensure economically meaningful credit proportions. The effects of sectoral concentration and diversification on profitability are controversial (Acharya et al., 2006; Tabak et al., 2011). Therefore, no clear expectation is established regarding the sign of the coefficient associated with this variable. The significance of this parameter will inform RQ2.

As for the control variables, the vector $X_{i,t}$ includes traditional determinants of bank profitability[2]. Bank size (*Size*) is measured by the logarithm of total assets, which captures potential economies of scale (Goddard et al., 2004). The capitalisation ratio (*Capital_Ratio*) is introduced as an indicator of financial soundness (or the degree of leverage), loss-absorption capacity. Operational efficiency (*Cost_Income*) is calculated using the cost-to-income ratio, and should display a negative relationship with profitability. The specification also controls for credit risk (*Credit_Risk*), funding structure (*Deposit_Ratio*), and loan portfolio composition through the shares of mortgage lending (*Mortgage_sh*) (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999).

In addition to the banks' fixed effects, annual fixed effects (λ_t) are included in all model specifications. These effects reflect common macroeconomic conditions, changes in monetary policy and interest rates, regulatory developments and adverse shocks affecting the economy, which tend to influence banks' profitability over time. By taking into account the specific influences of each year, it is possible to analyse the relationship between sectoral credit allocation and banks' performance more accurately, thereby reducing the risk of omitted variable bias arising from unobserved time-dependent factors.

The introduction of μ_i allows for the capture of bank-specific fixed (time-invariant) effects, and $\varepsilon_{i,t}$ represents the idiosyncratic error term.

4.2.2. Crisis Model Specification

To analyse the relationship between banks' exposure to the real estate and construction sectors and bank profitability during periods of economic and financial distress, an extension

[2] Detailed definitions, construction procedures and treatment of all variables are reported in Appendix B.

of the base model is estimated by introducing variables related to periods of crisis. This specification allows us to assess whether the impact of exposure to the real estate and construction sectors on bank profitability differs during crisis periods.

The econometric model assumes the following specification:

$$
\begin{aligned}
Profitability_{i,t} &= \alpha + \beta_1 Profitability_{i,t-1} + \beta_2 RECExposure_{i,t} \\
&+ \beta_3 HHI_{i,t} + \delta_1 GFC_t + \delta_2 Sovereign_t + \delta_3 Covid_t \\
&+ \delta_4 \left(RECExposure_{i,t} \times GFC_t\right) \\
&+ \delta_5 \left(RECExposure_{i,t} \times Sovereign_t\right) \\
&+ \delta_6 \left(RECExposure_{i,t} \times Covid_t\right) + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}
\end{aligned}
\qquad \textbf{(4.2.2.)}
$$

The remainder of the model structure is similar to that specified in the baseline model except for the crisis-specific dummy variables corresponding to the *GFC* (Global Financial Crisis: 2008–2010), the *Sovereign* (Sovereign Debt Crisis: 2011–2014) and the *Covid* (COVID-19 pandemic: 2020–2021). The dummy variables take the value one during episodes of crisis and zero in all other periods and the interaction variables with *RECExposure*.

These periods are defined with reference to major episodes of economic and financial distress that significantly affected financial markets, credit conditions and banking activity. We consider three crisis episodes: the Global Financial Crisis (2008–2010), which reflects the disruption in international financial markets (Jordà et al., 2013; Schularick & Taylor, 2012); the Sovereign Debt Crisis (2011–2014), which corresponds to a period of heightened sovereign risk and financial instability across several European economies (European Central Bank, 2011; Fratianni & Marchionne, 2017); and, most recently, the COVID-19 pandemic (2020–2021), associated with the economic disruption caused by the pandemic and the extraordinary monetary, fiscal and regulatory measures implemented in response (European Central Bank, 2022b).

Following the COVID-19 pandemic, the post-pandemic period was also characterised by rising inflation, tighter monetary policy and heightened geopolitical uncertainty following the Russian invasion of Ukraine. These developments altered financing conditions, increased economic uncertainty and contributed to a rapid rise in interest rates across the euro area, with potential implications for banking activity and profitability (European Central Bank, 2023b; European Systemic Risk Board, 2023).

The interaction variables between the *RECExposure* variable and each crisis dummy variable, allow to analyse whether the impact of exposure to the real estate and construction sectors on bank profitability varies for these crisis episodes. This specification allows us to test hypothesis H3 by examining whether this impact varies during periods of economic and financial distress. A statistically significant interaction coefficient would indicate that the relationship between sectoral credit allocation and profitability changes during the corresponding crisis episode. Given the mixed evidence in the literature regarding the profitability effects of sectoral exposure, no prior expectation is imposed on the sign of these interaction coefficients (Albertazzi & Gambacorta, 2009; Azevedo et al., 2022).

While year fixed effects control for common macroeconomic shocks affecting all banks, the crisis dummies and interaction terms allow us to explicitly examine whether the relationship between *RECExposure* and profitability changes during specific crisis episodes (Verbeek, 2017; Wooldridge, 2002).

The coefficients associated with the crisis dummies capture the direct effect of each crisis episode on bank profitability. In general, periods of economic and financial distress are expected to exert downward pressure on profitability through higher credit risk, weaker lending activity and a deterioration in borrowers' repayment capacity (Albertazzi & Gambacorta, 2009; Bolt et al., 2012; Dietrich & Wanzenried, 2011). Therefore, a negative relationship between crisis periods and bank profitability may be expected.

While these crisis periods are defined in accordance with the literature, it is important to acknowledge that fixed time intervals may not fully capture the effects of economic and financial crises and may vary across institutions and over time.

According to the literature, adverse shocks tend to reduce bank profitability and lead to a contraction in credit supply, commonly referred to as a credit crunch (Bernanke & Lown, 1991). Banks are therefore not only affected by crises but may also amplify their effects on the economy. Profitability may decline due to higher default rates, increased impairment charges and lower lending activity during periods of deleveraging (Ivashina & Scharfstein, 2010; Peek & Rosengren, 1995).

4.3. Estimation Methods

The estimation of the models presented in the previous section uses panel data techniques in order to simultaneously account for unobserved heterogeneity across banks and the time-series dynamics of banks' profitability. Given the structure of the data, the pooled ordinary least squares (POLS) method is not considered, as it would disregard the unobserved heterogeneity between banks[3].

Examples of unobservable characteristics of banking institutions are the business model, management practices, organisational structure and risk profile. As these parameters may be correlated with the explanatory variables, it is necessary to adopt an estimation approach capable of controlling for unobserved heterogeneity across banks (Verbeek, 2017; Wooldridge, 2002).

Consistent with the empirical framework described above, all specifications include year fixed effects to control for common shocks affecting all institutions over time. These effects capture factors such as changes in monetary policy, interest rate conditions, regulatory and supervisory developments, macroeconomic conditions and financial market developments.

To evaluate the most appropriate alternatives, the fixed-effects (FE) model and the random-effects (RE) model, we use the Hausman test. The test statistic rejects the null hypothesis of no correlation between the unobserved effects and the explanatory variables for ROA ($\chi^2(9)=168.88$, $p<0.001$) and NIM ($\chi^2(9)=125.74$, $p<0.001$) (Hausman, 1978). For the ROE specification, the standard Hausman test returned a negative test statistic, indicating that its asymptotic assumptions were not satisfied. These results reinforce the case for adopting fixed effects.[4]

As an additional diagnostic, multicollinearity was assessed using Variance Inflation Factors (VIF). The results indicate no evidence of severe multicollinearity among the explanatory variables, as all VIF values remain well below conventional threshold levels (Gujarati & Porter, 2009).[5]

The inclusion of a lagged dependent variable enables the model to capture the persistence of bank profitability over time. However, dynamic specifications may give rise to endogeneity

[3] POLS estimators are not appropriate in the presence of unobserved bank-specific heterogeneity potentially correlated with the explanatory variables.
[4] The complete Hausman test outputs are presented in Appendix D.
[5] Full VIF results are presented in Appendix E.

problems, particularly due to the potential correlation between the time-lagged dependent variable and the error term. Although this issue cannot be entirely eliminated, the larger the panel size, the smaller its magnitude tends to be. Given the relatively long time horizon of the sample, the use of a dynamic fixed-effects specification remains a widely used approach in the literature on the determinants of bank profitability (Athanasoglou et al., 2008; Goddard et al., 2004).

Although the banking literature frequently refers to dynamic models estimated using the Generalised Method of Moments (GMM), the characteristics of the present sample do not make GMM necessarily preferable to fixed-effects estimation. This method is suitable for contexts where there is a large number of units and a short time horizon (Baltagi, 2005; Roodman, 2009). However, in our case, the sample has an extended time horizon, which reduces the need to use instrument-based estimators. In this regard, the use of GMM may cause problems related to instrument proliferation and the fragility of validity tests (Arellano, 1987; Blundell & Bond, 1998; Roodman, 2009)[6].

To overcome the potential problems of heteroscedasticity and autocorrelation, standard errors are adjusted according to the clustering method at the banking institution level. This is a method that allows for reliable statistical inference and is widely used in empirical studies with panel data, using robust standard errors clustered at the bank level (Petersen, 2009)[7].

In conclusion, the estimation strategy applied uses fixed-effects models and cluster-robust standard errors to ensure the consistency and robustness of the results (Arellano, 1987; Wooldridge, 2002).

4.4. Data and Sample

This study focuses on the Portuguese banks. The banking sector in Portugal provides a relevant setting for analysing the relationship between sectoral credit allocation and bank profitability, given the importance of real estate and construction-related lending.

[6] Although dynamic banking models are frequently estimated using GMM techniques, the large time dimension of the sample reduces concerns regarding Nickell bias and limits the advantages of instrument-based estimators.
[7] Clustered standard errors are used at the bank level to allow for correlation of the error term within the same banking institution over time.

The financial system in Portugal shows considerable exposure to the real estate and construction sectors, which play a key role in credit dynamics and economic activity (European Commission, 2023). Real estate and construction activities account for a significant proportion of the total credit granted to non-financial companies. The Portuguese banking sector was significantly affected by episodes of financial instability in recent decades, illustrating its sensitivity to adverse economic and financial shocks (Banco de Portugal, 2023; Dias & Marques, 2018).

The European Central Bank (ECB) has reported that a significant proportion of loans granted to non-financial corporations are linked to the real estate and construction sectors, either directly or indirectly, given the use of real estate assets as collateral or the purpose of the financing (European Central Bank, 2022a, 2023a). According to the ECB, approximately one-third of loans to non-financial corporations in the euro area represented exposure to the sector in 2022, underscoring the systemic importance of this sector (European Central Bank, 2022b, 2023b). Later, in 2024, the ECB showed that euro area banks were raising around €1.3 billion in loans from investors in commercial real estate, which underscores the scale of this exposure (European Central Bank, 2024a, 2024b; European Systemic Risk Board, 2024).

4.4.1. The Portuguese Banking Context

The Portuguese banking system is bank-centered, with the financing of the economy relying heavily on banks. Financial and macroeconomic shocks not only constrain the volume of credit but also affect its distribution across different sectors and types of borrowers, which has consequences for banking risk, stability and profitability (Azevedo et al., 2022).

For Portugal, the significance of the real estate and construction sectors stems from historical and structural factors. In the pre-crisis period, credit growth was linked to an expansion in real estate financing, both in the residential sector and in construction and real estate activities. Rising real estate asset prices increased collateral values and supported further credit growth, strengthening the link between developments in the real estate market and banks' balance sheets. As a result, fluctuations in real estate prices became an important source of risk for the Portuguese banking sector (Azevedo et al., 2022; European Systemic Risk Board, 2017).

Credit allocation within the Portuguese banking system is not distributed evenly across companies and economic sectors. Based on data provided by the Central Credit Register of the Banco de Portugal, several studies have documented a misallocation of credit, in which a significant proportion of bank financing was to firms with low levels of productivity (Banco de Portugal, 2016).

Over the last few decades, Portugal has experienced several periods of economic and financial instability, such as the global financial crisis, the sovereign debt crisis and, more recently, the impact of the pandemic (Almeida & Sousa, 2025; Castro, 2013; European Central Bank, 2017).

The definition of the Sovereign Debt Crisis period deserves further clarification. While the timing of the Global Financial Crisis and the COVID-19 pandemic is relatively standard in the literature, the definition of the Sovereign Debt Crisis period is less clear-cut and may vary across studies and countries. In the Portuguese case, the period 2011–2014 is adopted because it coincides with the process of the Economic Adjustment Programme following the request for international financial assistance in 2011, marking the phase of greatest economic and financial adjustment for the banking sector (Banco de Portugal, 2016; Kincaid, 2016).

4.4.2. Data Source and Sample Construction

The data were provided by Banco de Portugal through the Banco de Portugal Microdata Research Laboratory (BPLIM). BPLIM provides detailed, consistent and harmonised information on the Portuguese banking sector (Banco de Portugal Microdata Research Laboratory (BPLIM), 2025).

We use the Portuguese Banking Sector Historical Series (SLB) and the Historical Central Credit Register (HCRC). The SLB dataset covers balance sheet data, income statements, lending activity, funding structure and other operational data. While HCRC is used to identify credit exposures by economic activity and construct the measure of exposure to the real estate and construction sectors. [8]

[8] The real estate and construction sectors are identified according to CAE Rev. 3 and include Division 41 (Construction of buildings), Division 42 (Civil engineering), Division 43 (Specialised construction activities), and Division 68 (Real estate activities).

The final dataset was constructed by combining bank-level information from the SLB database with sectoral credit information obtained from the HCRC. The linkage between the two databases was performed through the linkbank procedure available in BPLIM, allowing the integration of financial information at the bank level with data on credit exposures by economic activity. To ensure consistency across data sources, only matched observations were retained in the final sample. The resulting dataset was subsequently used to construct the variables employed in the empirical analysis (Banco de Portugal Microdata Research Laboratory (BPLIM), 2024, 2025).

The sample under consideration covers the period from 2009 to 2023, as the availability and consistency of the model's key variables are limited to this period. Although the Global Financial Crisis is commonly defined as the period 2008–2010, the empirical sample begins in 2009. Therefore, only the years 2009–2010 are observed in the analysis.

The final dataset takes the form of an unbalanced panel at the bank-year level, which reflects the structural behaviour of the banking sector in Portugal over the time horizon. Factors such as mergers, acquisitions, entries and exits of institutions, and limitations in the availability of data for some variables lead to differences across banks in the number of observations. The use of an unbalanced panel is quite common in literature, as it does not compromise the validity of the estimates provided that econometric models, such as the fixed-effects model, are used correctly (Baltagi, 2005).

In the baseline specification, the initial sample comprises 41 banking institutions. Due to mergers, market exits and missing observations for some variables, the effective estimation sample is reduced to around 39 banks, corresponding to approximately 370 bank-year observations. There is heterogeneity among banks in terms of size, funding structure and performance (Athanasoglou et al., 2008; Goddard et al., 2004)[9].

To construct the sample, it was necessary to exclude observations with missing or inconsistent values in the model's key variables, particularly profitability, exposure to the real estate sector, credit risk and some control variables.[10] This procedure ensures the data quality and the robustness of the econometric estimates, thereby reducing the possibility of bias

[9] Appendix A provides a detailed distribution of banks according to the number of observations available throughout the sample period.
[10] Observations with missing information in key variables were excluded from the final sample. Extreme values were subsequently treated through winsorisation, as described below.

related to measurement errors or incomplete aggregate information (Athanasoglou et al., 2008; Goddard et al., 2004).

Table 1 – Definition of Variables

Category	Variable	Definition
Dependent variables		
	ROA	Return on Assets
	ROE	Return on Equity
	NIM	Net Interest Margin
Main explanatory variables		
	RECExposure	Real Estate and Construction Credit Exposure
	HHI	Herfindahl-Hirschman Index
	GFC	Global Financial Crisis dummy
	Sovereign	Sovereign Debt Crisis dummy
	Covid	COVID-19 Crisis dummy
	RECExposure × *GFC*	Interaction variable
	RECExposure × *Sovereign*	Interaction variable
	RECExposure × *Covid*	Interaction variable
Control variables		
	Size	Logarithm of total assets
	Capital_Ratio	Tier 1 capital ratio (%)
	Cost_Income	Cost-to-income ratio
	Credit_Risk	Net credit impairment losses ratio
	Deposit_Ratio	Deposits over total assets
	Mortgage_sh	Share of mortgage credit

Notes: This table reports the definition of the variables used in the empirical analysis. All variables are constructed based on the raw data from the Banco de Portugal dataset (provided by BPLIM).

Table 1 presents the definition of the variables used in the econometric model. The variables were defined in line with the literature on the determinants of bank profitability and sectoral credit allocation[11].

Most variables were winsorised at the 1st and 99th percentiles to mitigate the influence of extreme observations. However, the *Capital_Ratio* exhibited a particularly skewed distribution

[11] Detailed definitions and construction procedures are provided in Appendix B.

with unusually high values. Therefore, a more restrictive winsorisation procedure at the 5th and 95th percentiles was applied to this variable to reduce the influence of extreme observations and obtain a more representative measure of bank capitalisation. In addition, *ROA* was bounded at economically plausible limits to reduce the influence of extreme profitability observations. These procedures affected only a limited number of observations and were implemented to improve the robustness of the empirical analysis without materially altering the overall distribution of the variables.

4.5. Variables and Descriptive Statistics

Exploratory data analysis is one of the key steps in understanding the characteristics of the sample and identifying preliminary patterns in the variables under study.

We present the descriptive statistics of the main variables in the empirical model, and a brief analysis of the evolution in the variables of interest, always focusing on banking profitability and the sectoral composition of credit portfolios.

4.5.1. Descriptive Statistics

This section presents the descriptive statistics for the main variables used in the empirical analysis.

Table 2 – Descriptive Statistics

Variable	Mean	Std. Dev.
ROA	0.0091	0.0218
ROE	0.0532	0.1435
NIM	0.0205	0.0134
RECExposure	0.2152	0.1583
HHI	0.5167	0.1818
Size	7.4624	2.2484
Capital_Ratio (%)	20.5205	11.8899
Cost_Income	0.6011	0.2428
Credit_Risk	0.0138	0.0392
Deposit_Ratio	0.5216	0.2916

Mortgage_sh	0.4269	0.3625

Notes: The statistics are based on the effective estimation sample of Portuguese banks over the period 2009–2023. All variables are constructed from data obtained through the BPLIM, combining information from the SLB and the HCRC. Continuous variables were winsorised to reduce the influence of extreme observations. Specifically, most variables were winsorised at the 1st and 99th percentiles, while *Capital_Ratio* was winsorised at the 5th and 95th percentiles. Minimum and maximum values are not reported due to Banco de Portugal (BPLIM) disclosure requirements, which restrict the release of statistics that could facilitate the identification of individual institutions.

Table 2 shows that, on average, over the sample period, banks in Portugal observed *ROA* of 0.91% and a *ROE* of 5.32%. As for *NIM*, it stands at an average of 2.05%.

As for the variables of interest, *RECExposure* shows an average value of 0.22 and a standard deviation of 0.16, indicating marked dispersion. This suggests considerable heterogeneity in the sectoral composition of banks' credit portfolios across institutions and over time. Such variation is consistent with the cyclical behaviour commonly associated with credit markets (Kiyotaki & Moore, 1997). On the other hand, the *HHI* shows an average value of around 0.52, suggesting an intermediate level of concentration across the different economic sectors.

Furthermore, the control variables show significant heterogeneity across banks, particularly in terms of size, specialisation and operational efficiency. These characteristics may also vary over time within the same institution, reflecting changes in business strategy, balance-sheet structure, risk management practices and market conditions. Therefore, their inclusion in the empirical model is important to account for time-varying factors that may influence bank profitability (Boyd & Runkle, 1993; Maudos & Fernández de Guevara, 2004).

Size shows considerable variation, reflecting the coexistence of relatively small and large institutions within the Portuguese banking sector. *Cost_Income* exhibits significant variability, suggesting differences in operational efficiency across banks. *Deposit_Ratio* indicates that customer deposits constitute an important source of funding, although the wide range of values points to heterogeneity in funding structures. *Mortgage_sh* indicates that residential mortgage lending represents a substantial component of banks' credit portfolios.

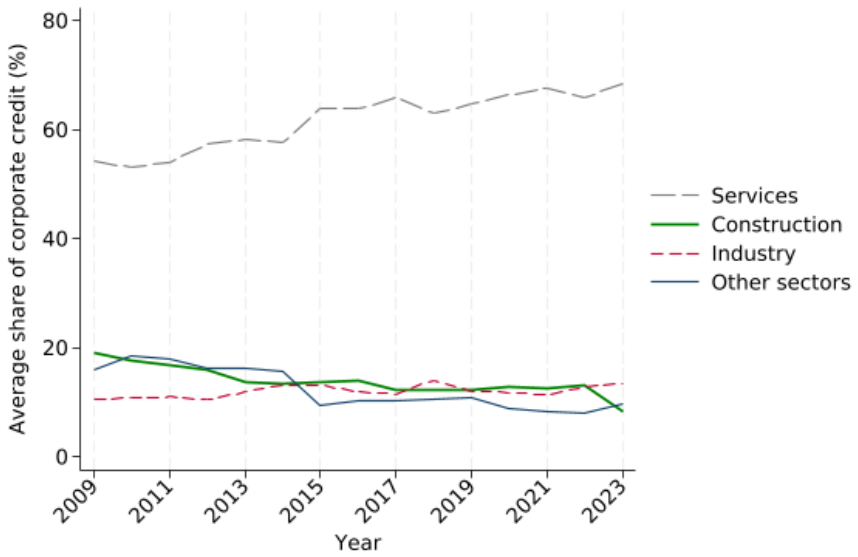
Capital_Ratio exhibits considerable variation across banks, suggesting important differences in capitalisation levels within the Portuguese banking sector. Such variation may reflect differences in business models, risk profiles, regulatory requirements and capital management strategies adopted by individual institutions (Abbondanza et al., 2025; Shim, 2013). *Credit_Risk* also displays substantial dispersion across observations, indicating heterogeneity in asset quality and risk management practices among Portuguese banks.

Appendix G shows the correlation matrix for the variables used in the empirical analysis. The results do not indicate the presence of severe multicollinearity among the explanatory variables, suggesting that the variables capture distinct dimensions of bank characteristics, lending behaviour and profitability.

4.5.2. Evolution of Key Variables

To complement the descriptive statistics analysis, this section examines the time-series evolution of the main variables included in the econometric model. This allows the identification of relevant trends and patterns over the period under review.

Figure 1 – Credit to Corporations Across Sectors (2009-2023)

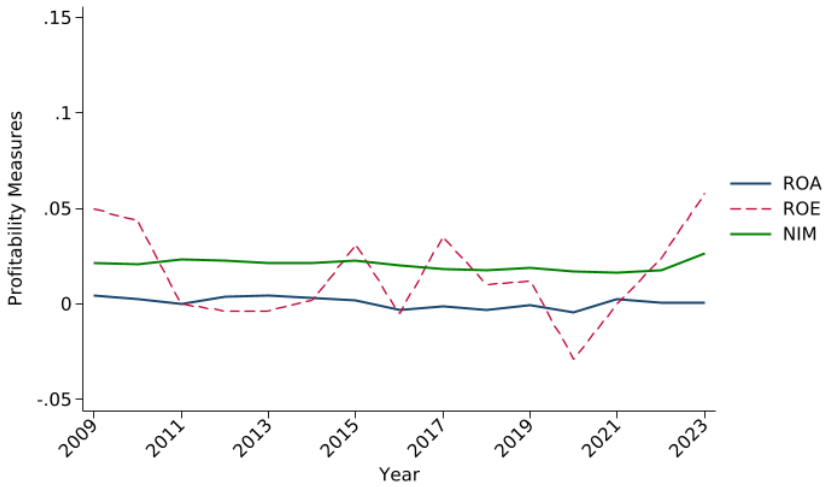


Source: Banco de Portugal (BPLIM), own calculations.
Notes: This figure reports the average annual distribution of corporate credit across economic sectors. Services, Industry and Construction are presented separately, while Other sectors aggregate Agriculture, Utilities and Other Activities. Shares are computed at the bank-year level and then averaged across banks.

Figure 1 presents the average across banks of the breakdown of credit to corporations for the major economic sectors between 2009 and 2023. Corporate credit is not uniformly distributed across economic sectors, and sectoral allocation patterns evolved over the analysed period. The services sector consistently accounts for the largest share of corporate credit, corresponding, on average, to more than half of total corporate credit. Industry and construction have considerably lower shares, although both are important beneficiaries of bank credit.

The figure also reveals some changes in the composition of business credit over time. The share attributed to services gradually increases, while the relative importance of construction decreases throughout the sample period. At the same time, the share of credit allocated to other sectors increased during the post-crisis period, suggesting a gradual reallocation of lending activities across economic sectors. This pattern is consistent with the adjustment process experienced by the Portuguese economy and banking sector following the correction of the real estate cycle and the subsequent deleveraging period, during which the relative importance of construction-related activities in bank lending portfolios declined (Banco de Portugal, 2021; Dias et al., 2016).

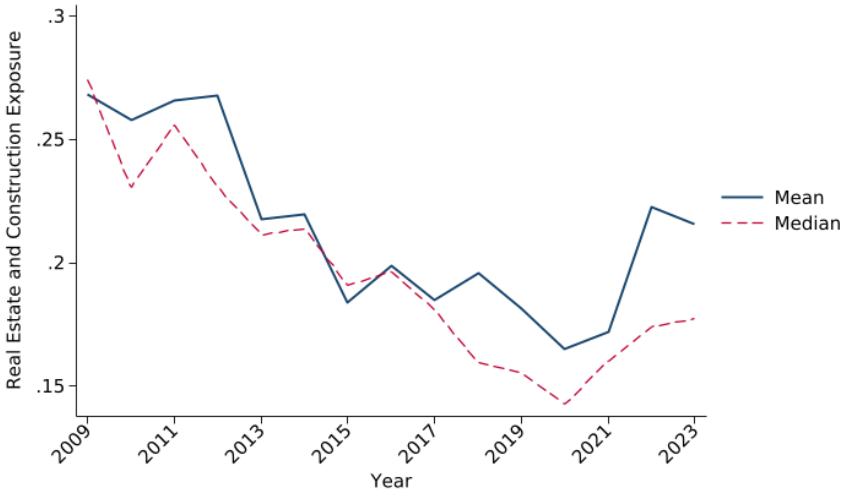
Figure 2 – Bank Profitability Measures (2009–2023)



Source: Banco de Portugal (BPLIM), own calculations.
Notes: The figure reports the evolution of the average profitability indicators of Portuguese banks between 2009 and 2023. ROA, ROE and NIM are measured as defined in Table 1. Variables are winsorised when appropriate.

The trends in the main indicators of banking profitability (*ROA*, *ROE* and *NIM*) are shown in *Figure 2*. The results reveal distinct patterns among the variables. *ROA* remains largely stable from 2009 to 2023, albeit at low levels, reflecting a low average return on banking assets. On the other hand, *ROE* shows significant volatility, with negative values during periods of greater financial instability (particularly during the COVID-19 pandemic). Finally, *NIM* follows a stable trajectory, highlighting the importance of traditional financial intermediation in generating financial results (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999).

Figure 3 – Credit Exposure to Real Estate and Construction Sectors (2009-2023)



Source: Banco de Portugal (BPLIM), own calculations.
Notes: The figure reports the yearly mean and median values of banks' exposure to the real estate and construction sectors across Portuguese banks over the period 2009–2023. Exposure is measured as the share of credit granted to non-financial corporations operating in the real estate and construction sectors relative to total corporate lending.

Figure 3 illustrates the evolution of the average and median exposure of Portuguese banks to the real estate and construction sectors between 2009 and 2023. The results indicate a gradual decline over the sample period, particularly between 2012 and 2020. This decline reflects the reduction in the relative importance of the real estate and construction sectors within credit portfolios, following the post-crisis adjustment process. From 2021 onwards, both the mean and the median show a moderate recovery, suggesting a partial increase in banks' exposure to real estate and construction lending. Throughout the period under review, the mean remains above the median, indicating that a relatively small number of banks maintained a comparatively higher exposure to these sectors. Overall, the pattern observed is consistent with the post-crisis restructuring of the Portuguese banking sector and with the gradual normalisation of lending following the deleveraging period (Kiyotaki & Moore, 1997; Schularick & Taylor, 2012).

Figure 4 – Credit Portfolio Sectoral Concentration (2009-2023)



Source: Banco de Portugal (BPLIM), own calculations.
Notes: The figure reports the yearly distribution of the Herfindahl-Hirschman Index (HHI) across Portuguese banks over the period 2009–2023. Higher values indicate greater concentration in sectoral credit allocation, while lower values reflect more diversified credit portfolios.

Figure 4 shows the *HHI* index over time. Based on the results, we observe that in pre-crisis periods, the composition of the loan portfolio was relatively more diversified. The results indicate a gradual increase in portfolio concentration from 2015 onwards, suggesting that banks allocated a larger proportion of corporate lending to a smaller number of economic sectors during the post-crisis period. The mean and median HHI have followed an upward trend since 2020, indicating that this pattern was common to all banks, rather than being driven by a few institutions. However, there was a slight decline in 2023, suggesting a more diversified allocation of corporate credit. Overall, these trends are consistent with the post-crisis adjustment of the Portuguese banking sector and with changes in the sectoral allocation of credit over time (Acharya et al., 2006).

Figure 5 - Evolution of Bank Size (Mean and Median Assets) (2009-2023)



Source: Banco de Portugal (BPLIM), own calculations.
Notes: This figure reports the evolution of the mean and median values of bank size, measured as the logarithm of total assets, between 2009 and 2023. Statistics are computed at the bank-year level and then averaged across

Figure 5 presents the evolution of the mean and median values of bank size, measured as the logarithm of total assets, between 2009 and 2023. Both indicators fluctuate throughout the sample period, with a decline during the years following the financial crisis and a moderate recovery towards the end of the sample.

The divergence between the mean and median values highlights the heterogeneity of the Portuguese banking sector, where a limited number of large banks account for a substantial share of total assets. This evidence supports the inclusion of bank size as a control variable in the empirical analysis, given that differences in scale may influence both profitability and lending behaviour.

5. Empirical Results and Discussion

In this chapter, we present the statistical results obtained from the estimation of the econometric models described in Chapter 4 and discuss the main findings in relation to the research questions and the existing literature.

5.1. Univariate Tests

To complement the analysis in the previous sections, the following is an additional analysis based on a comparison of the means of banking profitability across the different groups of observations. This approach makes it possible to provide preliminary evidence regarding the relationship between the concentration of loan portfolios, exposure to the real estate and construction sectors, and the performance of banking institutions.

To this end, the sample is divided into two groups to determine whether the loan portfolio concentration index *(HHI)* and the exposure to the real estate and construction sectors *(RECExposure)* lie above or below the median. Using this method, it is possible to distinguish between different credit allocation patterns and ascertain whether these are related to differences in bank profitability.

Table 3 – Difference *t*-test Loan Portfolio Concentration Subsamples

	HHI [Median = 0.436]			
	Above Median	Below Median	Difference	*p*-value
ROA	0.0020	-0.0003	-0.0023	0.2630
ROE	0.0386	-0.0100	-0.0486***	0.0004
NIM	0.0231	0.0175	-0.0056***	0.0000

Notes: This table reports univariate difference *t*-test statistics for profitability measures for bank-year observations with HHI is above and below the sample median. Difference is computed as Above Median minus Below Median. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3 shows the mean comparison tests for profitability measures across bank-year observations classified according to the median level of portfolio concentration (*HHI*).

According to the results, banks with a portfolio concentration above the median record higher average profitability in terms of *ROE* and *NIM*. Banks with the highest concentration record an average *ROE* of 3.86%, compared with –1.00% for banks below the median. On the other hand, the average *NIM* is 2.31% and 1.75%, respectively. Both differences are

statistically significant. In contrast, *ROA* shows no statistically significant difference, suggesting that differences in portfolio concentration are not associated with profitability.

Overall, these figures provide preliminary evidence that sector-level concentration of the loan portfolios may be associated with better performance in terms of profitability, particularly in terms of *ROE* and *NIM*.

Table 4 – Difference *t*-test Real Estate and Construction Credit Exposure Subsamples

	RECExposure [Median = 0.1559]			
	Above Median	Below Median	Difference	*p*-value
ROA	0.0044	-0.0011	0.0055**	0.0108
ROE	0.0326	0.0053	0.0273*	0.0554
NIM	0.0263	0.0171	0.0092***	0.000

Notes: This table reports univariate difference *t*-tests statistics for profitability measures for bank-year observations with *RECExposure* is above and below the sample median. Difference is computed as Above Median minus Below Median. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4 presents the tests comparing the means of profitability proxies for two subsamples of banks above and below the median level of *RECExposure*.

Banks with above-median exposure to the real estate and construction sectors record higher average profitability across all three performance measures. The average *ROA* is 0.44% for banks with above-median exposure, compared with −0.11% for banks with below-median exposure. The average *ROE* is 3.26% for banks with higher exposure, compared with 0.53% for banks with lower exposure. The average *NIM* stands at 2.63% and 1.71%, respectively. The differences are statistically significant for all measures of profitability. These results suggest that banks with greater exposure to the real estate and construction sectors tend to exhibit higher profitability.

5.2. Sectoral Allocation and Bank Profitability

In this section, we present and discuss the results of the multivariate analysis. The findings are organised into the baseline specification and the crisis specification

5.2.1. Baseline Results

The baseline specification serves as the point of reference for assessing the relationship between sector-specific credit allocation and bank profitability.

Table 5 – Baseline Model – Fixed Effects Regression Results

Variables	*ROA*	*ROE*	*NIM*
Lagged profitability	0.2200***	0.1340**	0.5290***
	(0.0917)	(0.0622)	(0.0922)
RECExposure	0.0101**	0.0116***	-0.0001
	(0.0046)	(0.0363)	(0.0026)
HHI	0.0067	0.0267	0.0030
	(0.0048)	(0.0412)	(0.0050)
Size	-0.0033**	-0.0276**	-0.0092***
	(0.0012)	(0.0130)	(0.0022)
Capital_Ratio	0.0001	0.0007	0.0000
	(0.0001)	(0.0006)	(0.0001)
Cost_Income	-0.0321***	-0.3800***	-0.0078***
	(0.0034)	(0.3300)	(0.0028)
Credit_Risk	-0.0858***	-1.1500***	0.0351***
	(0.0277)	(0.3300)	(0.0061)
Deposit_Ratio	0.0031	-0.0805	0.0080*
	(0.0073)	(0.0596)	(0.0043)
Mortgage_sh	-0.0017	-0.0954***	0.0027
	(0.0046)	(0.0349)	(0.0031)
2010 (Base Year)	(.)	(.)	(.)
2011	-0.0023	-0.0417*	0.0016
	(0.0019)	(0.0212)	(0.0011)
2012	0.0004	-0.0450	-0.0092
	(0.0020)	(0.0374)	(0.0012)
2013	0.0020	-0.0237	-0.0020*
	(0.0022)	(0.0210)	(0.0011)
2014	-0.0011	-0.0335	-0.0018
	(0.0032)	(0.0296)	(0.0018)
2015	0.0026	0.0190	-0.0024
	(0.0027)	(0.0267)	(0.0016)
2016	0.0012	-0.0032	-0.0021
	(0.0025)	(0.0290)	(0.0018)

2017	0.0021	0.0151	-0.0023
	(0.0023)	(0.0266)	(0.0019)
2018	0.0020	0.0138	-0.0018
	(0.0025)	(0.0238)	(0.0016)
2019	0.0013	0.0093	-0.0023
	(0.0024)	(0.0248)	(0.0016)
2020	-0.0020	-0.014	-0.0031*
	(0.0026)	(0.0235)	(0.0017)
2021	0.0006	0.0154	-0.0029*
	(0.0029)	(0.0266)	(0.0016)
2022	0.0012	0.0349	0.0002
	(0.0030)	(0.0281)	(0.0018)
2023	0.0009	0.0211	0.0077***
	(0.0030)	(0.0289)	(0.0025)
Constant	0.0398***	0.5270***	0.0785***
	(0.0124)	(0.1150)	(0.0188)
Observations	370	370	370
Banks	39	39	39

Notes: Robust standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The lagged dependent variable captures persistence in bank performance.

Table 5 presents the results of the baseline estimates for the three measures of banking performance: *ROA*, *ROE* and *NIM*.

The results show a high degree of persistence in bank profitability. This phenomenon is confirmed by the positive and statistically significant coefficient of the lagged dependent variable across all specifications. This result is consistent with the existing literature, showing that past performance is an important factor for current profitability.

Focusing on the main variable of interest, that tests H1, the exposure to credit granted to the real estate and construction sectors, *RECExposure* we find a positive and statistically significant effect on *ROA* and *ROE*, but not on *NIM*. These results suggest that greater exposure to the real estate and construction sectors is associated with higher bank profitability. The strongest effect is observed for *ROE*, while no statistically significant relationship is found for *NIM*.

The baseline results provide partial support for H1. Exposure to the real estate and construction sectors is positively associated with *ROA* and *ROE*, whereas no significant relationship is found for NIM. These findings suggest that exposure to the real estate and construction sectors contributes positively to bank profitability,

Concerning H2, the parameter associated with *HHI* is not statistically significant in any of the specifications. This result suggests that sectoral credit portfolio concentration is not systematically associated with bank profitability in the Portuguese banking sector. This evidence is consistent with the literature, which reports mixed results regarding the effects of portfolio sectoral concentration (Beck & Levine, 2002; Berger et al., 2010; Tabak et al., 2011).

Regarding the control variables, *Size* has a negative and statistically significant effect across all three profitability measures, suggesting that, after controlling for other bank-specific characteristics, larger banks tend to exhibit lower profitability (Pasiouras & Kosmidou, 2007; Trujillo-Ponce, 2013). *Capital_Ratio* is not statistically significant in any of the specifications, suggesting that differences in capitalisation are not systematically associated with bank profitability in the baseline models (Berger et al., 2010; Borio et al., 2017; Demirgüç-Kunt & Huizinga, 1999).

Cost_Income has a negative and highly significant effect in all specifications, as expected. *Credit_Risk* has a negative and significant impact on *ROA* and *ROE*, a result that is consistent with the adverse effect of credit deterioration on bank profitability documented in the literature (Borio et al., 2017; Castro, 2013; Demirgüç-Kunt & Huizinga, 1999). However, with regard to *NIM*, the variable is positive and significant. This result is consistent with previous studies documenting a positive relationship between risk-taking and net interest margins (Maudos & Fernández de Guevara, 2004; Trujillo-Ponce, 2013).

Deposit_Ratio is not statistically significant for either ROA or ROE, but it has a positive and marginally significant coefficient for NIM. These results suggest that greater reliance on deposits is associated with higher net interest margins, which is consistent with the literature (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999).

Mortgage_sh is negative and statistically significant for ROE, suggesting that banks with a higher proportion of mortgage lending tend to have lower ROE. No statistically significant relationship is found for ROA or NIM.

Overall, the baseline results show that exposure to the real estate and construction sectors plays an important role in explaining bank profitability. While *RECExposure* is positively associated with *ROA* and *ROE*, no significant relationship is found for *NIM*. Furthermore, no evidence is found that sectoral credit concentration affects bank profitability. Finally, operational efficiency and credit risk emerge as key determinants of bank performance.

5.2.2. Crisis Effects

We now analyse whether the relationship between sectoral credit allocation and profitability has changed during periods of financial instability, such as the Global Financial Crisis, the Sovereign Debt Crisis and the COVID-19 pandemic.

Table 6 – Crisis Model – Fixed Effects Regression Results

Variable	*ROA*	*ROE*	*NIM*
Lag profitability	0.2170**	0.1320**	0.5240***
	(0.0908)	(0.0632)	(0.0933)
RECExposure	0.0017	0.0864	0.0019
	(0.0069)	(0.0600)	(0.0020)
GFC	-0.0032	-0.0555	-0.0074**
	(0.0039)	(0.0375)	(0.0031)
Sovereign	-0.0037	-0.0521***	-0.0089***
	(0.0027)	(0.0189)	(0.0019)
COVID-19	-0.0021	-0.0260	-0.0107***
	(0.0013)	(0.0159)	(0.0018)
RECExposure × *GFC*	0.0160	0.1560	-0.0033
	(0.0126)	(0.1270)	(0.0056)
RECExposure × *Sovereign*	0.0126**	-0.0008	-0.0040
	(0.0055)	(0.0567)	(0.0040)
RECExposure × *COVID-19*	0.0109***	0.1020**	0.0002
	(0.0035)	(0.0417)	(0.0026)
HHI	0.0057	0.0368	0.0036
	(0.0048)	(0.0455)	(0.0047)
Size	-0.0030*	-0.0281**	-0.0094***
	(0.0017)	(0.0132)	(0.0023)

Capital_Ratio	0.0001*	0.0002	0.0000
	(0.0001)	(0.0007)	(0.0001)
Cost_Income	-0.3220***	-0.3820***	-0.0079***
	(0.0033)	(0.0689)	(0.0028)
Credit_Risk	-0.0898***	-1.1630***	0.0359***
	(0.0301)	(0.3390)	(0.0062)
Deposit_Ratio	0.0064	-0.0744	0.0681
	(0.0077)	(0.0674)	(0.0046)
Mortgage_sh	0.0022	-0.0991**	0.0012
	(0.0043)	(0.0429)	(0.0032)
2010 (Base Year)	(.)	(.)	(.)
2011	-0.0012	-0.0069	0.0034**
	(0.0028)	(0.0257)	(0.0013)
2012	0.0015	-0.0105	0.0009
	(0.0025)	(0.0322)	(0.0015)
2013	0.0032	0.0098	-0.0003
	(0.0030)	(0.0197)	(0.0014)
2014	(.)	(.)	(.)
2015	0.0024	-0.0007	-0.0103***
	(0.0021)	(0.0147)	(0.0017)
2016	0.0010	-0.0231	-0.0099***
	(0.00235)	(0.0229)	(0.0016)
2017	0.00154	-0.0059	-0.0101***
	(0.0030)	(0.0222)	(0.0014)
2018	0.0014	-0.0075	-0.0096***
	(0.0019)	(0.0167)	(0.0015)
2019	0.0006	-0.0119	-0.0101***
	(0.0014)	(0.0136)	(0.0015)
2020	-0.0027**	-00287**	-0.0002
	(0.0011)	(0.0106)	(0.0006)
2021	(.)	(.)	(.)
2022	0.0005	0.0147	-0.0076***
	(0.0010)	(0.0124)	(0.0013)

2023	(.)	(.)	(.)
Constant	0.0358**	0.5490***	0.0885***
	(0.0162)	(0.1290)	(0.021)
Observations	370	370	370
Banks	39	39	39

Notes: Robust standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. GFC refers to the Global Financial Crisis (2009–2010), Sovereign Crisis refers to the European Sovereign Debt Crisis (2011–2014), and COVID-19 Crisis refers to the COVID-19 pandemic period (2020–2021). Crisis variables are dummy indicators equal to one during the corresponding period and zero otherwise.

Based on *Table 6*, the results indicate that the coefficients associated with the main variable of interest, *RECExposure*, are no longer statistically significant as soon as the interaction terms with the crisis periods are introduced. This result suggests that the effect of exposure to the real estate and construction sectors is now contingent on the interaction terms specific to each crisis.

The crisis dummies indicate that the *Sovereign* and the *COVID-19* pandemic were associated with lower levels of profitability. The effects of the Sovereign Debt Crisis are statistically significant for *ROE*, whereas the *COVID-19* dummy is negative and statistically significant for *NIM*. The coefficient associated with the *GFC* is not statistically significant. Furthermore, the interaction terms allow us to assess whether the impact of sectoral credit allocation on bank profitability changes during periods of financial distress.

For the Global Financial Crisis, no statistically significant effects are observed for any of the profitability measures. Therefore, there is no evidence that this period significantly impacted the relationship between *RECExposure* and bank profitability in Portugal.

The interaction between *RECExposure* and *COVID-19* is positive and statistically significant for *ROA* and weakly significant for *ROE,* while remaining insignificant for *NIM*. These results suggest that the positive association between *RECExposure* and profitability became stronger during the pandemic for accounting-based profitability measures.

On the other hand, the interaction terms associated with the Sovereign Debt Crisis are positive and statistically significant for *ROA*, while remaining insignificant for *ROE* and *NIM*. This finding suggests that the positive association between *RECExposure* and profitability strengthened during the Sovereign Debt Crisis when profitability is measured by *ROA*.

The results provide limited support for H3. No significant interaction effects are observed during the Global Financial Crisis, while some evidence of changes in the relationship between *RECExposure* and profitability is found during the Sovereign Debt Crisis and the *COVID-19* pandemic.

The control variables remain consistent with the baseline specification. In general, they have the same sign and level of significance, with only minor changes in the statistical significance of some control variables. These results suggest that the main determinants of bank profitability remain robust after controlling for periods of financial instability.

Additional robustness checks, presented in Appendix F, confirm that the main conclusions remain qualitatively unchanged when an alternative model specification is applied. These results reinforce the robustness of the empirical findings.

In short, the analysis of the crisis suggests that periods of financial instability influence the relationship between lending to the real estate and construction sectors and bank profitability. However, the effects vary depending on the crisis episodes and the profitability indicators. Thus, macroeconomic conditions must be taken into account when assessing the implications of sectoral credit exposure on profitability.

5.3. Discussion of Results

The results of our study suggest that exposure to the real estate and construction sectors emerges as a key determinant of banks' performance in Portugal. The positive association between *RECExposure* and profitability, particularly when measured through *ROA* and *ROE*, suggests that greater exposure to these sectors is associated with higher bank profitability, which is consistent with the literature, highlighting the role of secured credit and the importance of the real estate and construction markets for banking activity (Allen & Gale, 2000; Kiyotaki & Moore, 1997).

These findings are relevant to the Portuguese context, given that the banking sector has maintained strong links with the real estate and construction markets. Rather than reflecting a purely cyclical phenomenon, the results suggest the existence of a broader structural relationship between sectoral credit allocation and banking performance. This evidence is consistent with the literature, which shows that credit related to the real estate and

construction sectors may increase profitability (Kiyotaki & Moore, 1997; Rajan & Winton, 1995).

This conclusion is particularly relevant given the period covered by the analysis. Between 2009 and 2023, the Portuguese banking sector underwent major changes, ranging from the Global Financial Crisis and the Sovereign Debt Crisis to major regulatory reforms and prolonged periods of exceptionally low interest rates (Banco de Portugal, 2026; Carmichael & Coën, 2018; Martins et al., 2016). The exposure to the real estate and construction sectors is positively associated with profitability, particularly when profitability is measured through *ROA* and *ROE*. Although the results indicate variations depending on periods of financial instability, the overall data show that these sectors continue to play an important role in the Portuguese banking system.

With regard to our second research question, results do not show that portfolio concentration is, by itself, a significant determinant of profitability. Although previous studies present conflicting evidence regarding the benefits of concentration (Acharya et al., 2006; Tabak et al., 2011; Winton, 2000), the findings suggest that, in the Portuguese context, bank profitability depends more on the specific sectors receiving credit than on how lending is distributed across sectors. Moreover, the literature argues that higher profitability associated with more concentrated portfolios may simply reflect compensation for higher risk exposure rather than superior performance. Since HHI is not statistically significant across the estimated specifications, the results provide little evidence that concentration alone generates either profitability gains or losses for Portuguese banks.

One possible explanation for these results is that Portuguese banks were subject to significant adjustments in their lending policies and regulatory requirements over the period under review. Following the financial and sovereign debt crises, banks were required to strengthen their capital positions and risk management practices and to reduce vulnerabilities (Banco de Portugal, 2024; European Central Bank, 2022a). In this context, differences in portfolio concentration may have become less relevant to profitability than the characteristics of the sectors receiving credit. This evidence is consistent with the literature which argues that bank profitability depends not only on internal decisions, but also on the economic and financial context (Staikouras & Wood, 2004).

Finally, the analysis of the crisis suggests that the relationship between sectoral credit exposure and profitability is influenced by the surrounding macroeconomic context, although the effects vary across different crisis episodes. No major changes were observed during the Global Financial Crisis, but the Sovereign Debt Crisis and the COVID-19 pandemic are associated with changes in the relationship between *RECExposure* and profitability for some measures. These findings suggest that the implications of sectoral credit exposure on returns depend not only on the composition of the portfolio, but also on the broader economic and financial context. This interpretation is consistent with the literature on financial cycles, which argues that macroeconomic conditions shape the risk-return profile of bank credit (Jordà et al., 2013; Schularick & Taylor, 2012).

In addition to the key variables of interest, the results confirm the importance of the traditional determinants of bank profitability. Operational efficiency and credit quality are the most consistent explanatory factors across all specifications. The size of a bank is also a significant determinant of profitability, indicating that differences in scale continue to influence bank profitability. The negative effects associated with *Cost_Income* and *Credit_Risk* reinforce the idea that profitability depends on portfolio composition, effective cost management and prudent risk-taking. These conclusions are in line with the established literature on the determinants of bank profitability (Pasiouras & Kosmidou, 2007; Trujillo-Ponce, 2013).

6. Conclusions

This dissertation analyses the relationship between the sectoral allocation of credit and bank profitability in Portugal over the period from 2009 to 2023, paying particular attention to the exposures to the real estate and construction sectors, the level of concentration in credit portfolios, and the impacts of periods of financial crisis. Using bank-year panel data for Portuguese banks provided by Banco de Portugal (BPLIM) and dynamic fixed-effects models with clustered robust standard errors, the study provides evidence that sectoral credit allocation plays an important role in explaining differences in bank performance.

First, the results indicate a positive relationship between *RECExposure* and profitability when performance is measured through *ROA* and *ROE*. Banks that experienced higher exposure to the real estate and construction sectors tended to report stronger profitability, highlighting the economic importance of these activities within the Portuguese banking system.

Second, the *HHI* measuring portfolio sectoral concentration is not statistically significant in the estimated specifications. This finding suggests that the implications of sectoral exposure on profitability depend more on the sectors receiving credit than on the overall degree of concentration in banks' credit portfolios.

Third, we highlight the variations observed across different periods of financial instability. The interaction between *RECExposure* and the *GFC* is not statistically significant, but some evidence of changes emerges during the Sovereign Debt Crisis and the COVID-19 pandemic. Results suggest that the profitability implications of sectoral credit exposure depend on the broader macroeconomic environment.

The results also confirm the importance of traditional determinants of bank profitability. Operational efficiency, bank size and credit quality emerge as consistent explanatory factors across all specifications, highlighting the role of effective cost management and prudent risk-taking in sustaining bank performance.

This dissertation contributes to the literature on bank profitability by focusing on the sectoral allocation of credit rather than on aggregate credit dynamics. While much of the existing literature emphasises bank-specific and macroeconomic determinants of profitability, this study highlights the importance of considering how credit is distributed across economic sectors.

A second contribution relates to the Portuguese context. By analysing the period between 2009 and 2023, the study provides updated evidence for a banking system that experienced major structural changes, such as the Global Financial Crisis, the Sovereign Debt Crisis, significant regulatory reforms and the COVID-19 pandemic. This extended timeframe allows for the assessment of the relationship between sectoral lending patterns and profitability under different economic and financial conditions.

Finally, the study contributes to the debate on specialisation and diversification in banking. Although previous studies provide mixed evidence regarding the profitability implications of portfolio concentration, the results are inconclusive for the Portuguese case.

The results obtained are highly relevant, but it is important to acknowledge some limitations associated with the research. The empirical analysis focuses on accounting profitability indicators and proxy variables that may not fully capture the risk underlying sectoral exposure. Despite the use of fixed-effects models and lagged variables to mitigate some endogeneity issues, it is not possible to rule out the existence of reverse causality or omitted variables. Moreover, whether the empirical models include a comprehensive set of control variables, some relevant determinants of profitability may have been omitted.

In this regard, it is important to note that the empirical analysis focuses exclusively on the Portuguese context, which naturally limits the extent to which the findings can be generalized to other banking systems. Even so, focusing on a single country enables a more detailed and consistent analysis of the specific institutional and economic environment, which is appropriately suited to the research objectives.

Another limitation is the level of aggregation of the data. The analysis uses information at the bank level and does not capture the characteristics of individual loans, such as maturity date, collateral, or borrower risk profiles. Consequently, potential differences in the quality and risk of credit exposures are not directly assessed.

A further limitation concerns the definition of crisis periods, which is based on fixed dummy variables. These periods were identified in line with the empirical literature, but the effects of economic and financial crises may not coincide exactly with the predefined time intervals and may vary from institution to institution. Consequently, the crisis dummy variables may not accurately capture the timing and intensity of crisis-related effects on bank profitability.

In addition, the main variable of interest is calculated on the basis of net amounts, taking into account the effects of accumulated impairment losses and write-offs. As such, it may not fully reflect the banks' gross exposure to the real estate and construction sectors.

Another limitation is the omission of specific macroeconomic variables that may influence bank profitability, such as interest rates and monetary policy conditions. To account for period-specific common effects, the empirical models include time-specific fixed effects, but this approach does not allow the individual effects of specific macroeconomic factors to be identified.

Future research could explore the relationship between sectoral credit allocation and financial stability in greater depth. Although this study focuses on profitability, future analyses could examine whether the profitability benefits associated with lending to the real estate and construction sectors are accompanied by higher levels of risk, for example, during periods of financial stress. Furthermore, future research could also investigate whether stock and flow measures of sectoral exposure yield different implications for bank performance.

Another avenue for future research would be the use of more detailed data. Loan-level data could include information on borrower characteristics, as well as the quality of collateral and credit risk, thereby enabling a better understanding of the channels through which the sectoral allocation of credit influences profitability.

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8. Appendices

Appendix A - Distribution of Banks by Number of Observations

Number of Years	Number of Banks	Percentage (%)
15–20 years	20	51.28
10–14 years	5	12.82
<10 years	14	35.90
Total	39	100.00

Notes: This table reports the distribution of banks according to the number of years they are observed in the sample. Banks are anonymized using identifiers provided by Banco de Portugal (BPLIM) due to confidentiality restrictions. The initial sample includes 41 banks; however, due to missing observations in some variables, the effective estimation sample is reduced to 39 banks.

Appendix B - Variable Construction and Definitions

Variable	Formula	Description	Treatment
ROA	$\frac{Net\ Income}{Total\ Assets}$	Return on Assets	Manually bounded at lower and upper limits
ROE	$\frac{Net\ Income}{Equity}$	Return on Equity	None
NIM	$\frac{Net\ Interest\ Income}{Earning\ Assets}$	Net Interest Margin	None
RECExposure	$\frac{REC\ Credit}{Total\ Corporate\ Credit}$[12]	Share of REC corporate credit	Winsorised (1st-99th percentiles)
HHI	$\sum Share_s^2$	Sectoral concentration	Constructed from sectoral credit shares
Size	$\log(Total\ Assets)$	Bank size	None
Capital_Ratio	$\frac{Tier\ 1\ Capital}{Risk-Weighted\ Assets}$	Capital adequacy measure	Winsorised (5th-95th percentiles)

[12] *REC credit* corresponds to the annual stock of performing corporate credit granted by each bank to firms classified under CAE Rev. 3 Divisions 41–43 (Construction) and Division 68 (Real Estate Activities). Credit amounts are aggregated at the bank-year level using the HCRC database. Total corporate credit is computed as the annual stock of performing corporate credit granted to all non-financial corporations. RECExposure is then calculated as the ratio between REC *credit* and total corporate credit.

Cost_Income	$\frac{Operating\ Expenses}{Operating\ Income}$	Operational efficiency	Winsorised (1st–99th percentiles)
Credit_Risk	$\frac{Credit\ Impairment\ Losses}{Domestic\ Credit}$	Net credit impairment losses ratio	Winsorized (1st-99th percentiles)
Deposit_Ratio	$\frac{Deposits}{Total\ Assets}$	Funding structure	None
Mortgage_sh	$\frac{Mortgage\ Credit}{Total\ Credit}$	Share of mortgage lending	None

Notes: This appendix reports the construction, definition and treatment of the main variables used in the empirical analysis. Continuous variables were winsorised to mitigate the influence of extreme observations. Most winsorised variables were treated at the 1st and 99th percentiles, while the capital ratio was winsorised at the 5th and 95th percentiles due to its more skewed distribution and unusually large observations. ROA was manually bounded at economically plausible limits. All variables are constructed using BPLIM.

Appendix C - Database Variables and Sources

Database	Variable Code	Description	Variable Used
QA1	QA1_16	Total Liabilities	*ROA; Size; Deposit_Ratio*
QA1	QA1_17	Total Equity	*ROA; Size; Deposit_Ratio*
QA1	QA1_13	Deposits	*Deposit_Ratio*
QA1	QA1_11	Earning Assets	*NIM*
QA2	QA2_16	Net Income	*ROA; ROE*
QA2	QA2_3	Net Interest Income	*NIM*
QA2	QA2_8	Operating Income	*Cost_Income*
QA2	QA2_9 + QA2_10	Operating Expenses	*Cost_Income*
QA2	QA2_12_2_1	Impairments	*Credit_Risk*
QA3	QA3_4	Tier 1 Capital Ratio (%)	*Capital_Ratio*
QB1	QB1_1_1_1_1	Agriculture Credit	*HHI*
QB1	QB1_1_1_1_2	Industrial Credit	*HHI*
QB1	QB1_1_1_1_3	Construction Credit	*HHI*
QB1	QB1_1_1_1_4	Utilities Credit	*HHI*
QB1	QB1_1_1_1_5	Services Credit	*HHI*
QB1	QB1_1_1_1_6	Other Credit	*HHI*
QB1	QB1_1_1_3_1	Mortgage Credit	*Mortgage_sh*

HCRC	valor_reg	Regular Credit Outstanding	*RECExposure*
HCRC	cae3	Economic Activity Classification (CAE Rev.3)	*RECExposure*

Notes: This appendix reports the main variables extracted from the Banco de Portugal database (BPLIM) and their respective codes used in the empirical analysis. QA1 contains balance-sheet information, QA2 includes income statement variables, QA3 contains capitalization indicators, and QB1 reports sectoral credit allocation data. In addition, the HCRC is used to construct the *RECExposure* variable by identifying firms classified under CAE Rev.3 categories F (Construction) and L (Real Estate Activities) and aggregating regular credit exposures (valor_reg) at the bank-year level. The listed variables were used in the construction of the profitability, concentration and control variables included in the econometric models.

Appendix D - Hausman Specification Test

Model	χ^2(df=9)	p-value	Preferred Model
ROA	168.88	0.000	FE
ROE	-196.61	-	-
NIM	125.74	0.000	FE

Notes: The Hausman specification test compares the fixed-effects (FE) and random-effects (RE) estimators. The null hypothesis is that differences in coefficients are not systematic. For the ROA and NIM specifications, the null hypothesis is rejected ($p < 0.001$), supporting the use of the fixed-effects estimator. The ROE model produced a negative test statistic, indicating that the standard Hausman test assumptions were not satisfied. Consistent with the ROA and NIM results and the empirical strategy adopted throughout the study, the fixed-effects model was retained.

Appendix E - Variance Inflation Factors (VIF)

Variable	VIF
Size	3.48
Mortgage_sh	3.22
Cost_Income	1.97
Capital_Ratio	1.87
L..ROA	1.83
HHI	1.64
Deposit_Ratio	1.50
RECExposure	1.20
Credit_Risk	1.13
Mean VIF	1.98

Notes: This table reports the Variance Inflation Factors (VIF) for the explanatory variables included in the baseline regression model. VIF values below conventional thresholds indicate the absence of significant multicollinearity.

Appendix F - Robustness Analysis Using *ln_RECCredit*

Variable	ROA	ROE	NIM
Lagged Profitability	0.251**	0.139**	0.521***
	(0.0959)	(0.0682)	(0.0958)
ln_RECCredit	0.00478	0.0106**	0.000217
	(0.00495)	(0.00490)	(0.000159)
HHI	0.00775	0.0491	0.00360
	(0.00544)	(0.0454)	(0.00499)
Size	-0.00395**	-0.0400***	-0.00943***
	(0.00168)	(0.0131)	(0.00222)
Capital_Ratio	0.000106	0.000531	0.0000533
	(0.0000914)	(0.000709)	(0.0000563)
Cost_Income	-0.0313***	-0.405***	-0.00935***
	(0.00385)	(0.0736)	(0.00286)
Credit_Risk	-0.0853***	-1.270***	0.0313***
	(0.0284)	(0.323)	(0.00473)
Deposit_Ratio	0.00692	-0.0255	0.00933**
	(0.00715)	(0.0532)	(0.00410)
Mortgage_Share	-0.00111	-0.100**	0.00198
	(0.00501)	(0.0383)	(0.00299)
2010 (Base Year)	(.)	(.)	(.)
2011	-0.00194	-0.0413*	0.00149
	(0.00197)	(0.0217)	(0.00187)
2012	0.00100	-0.0445	-0.000775
	(0.00225)	(0.0386)	(0.00114)
2013	0.00166	-0.0264	-0.00203*
	(0.00223)	(0.0217)	(0.00183)
2014	-0.00149	-0.0406	-0.00191
	(0.00310)	(0.0306)	(0.00181)
2015	0.00182	0.00986	-0.00240
	(0.00252)	(0.0272)	(0.00156)
2016	0.00429	-0.0136	-0.00217
	(0.00252)	(0.0300)	(0.00182)
2017	0.00137	0.00335	-0.00286
	(0.00236)	(0.0233)	(0.00179)
2018	0.00508	0.00257	-0.00186
	(0.00240)	(0.0249)	(0.00159)
2019	0.00563	0.00132	-0.00237
	(0.00241)	(0.0263)	(0.00163)
2020	-0.00275	-0.0211	-0.00316*
	(0.00263)	(0.0257)	(0.00164)
2021	0.000108	0.00672	-0.00303*
	(0.00289)	(0.0287)	(0.00161)
2022	0.000215	0.0211	-0.000178

	(0.00309)	(0.0301)	(0.00182)
2023	-0.000181	-0.000266	0.00710***
	(0.00313)	(0.0319)	(0.00244)
Constant	0.0342**	0.410***	0.0759***
	(0.0135)	(0.125)	(0.0185)
Observations	365	365	365
Banks	39	39	39

Notes: This table reports the results of the baseline fixed-effects regression using *ln_RECCredit*, defined as the natural logarithm of the total amount of credit granted to the real estate and construction sectors, as the main explanatory variable. The dependent variables are ROA, ROE and NIM. All specifications include lagged profitability, HHI, bank-specific control variables and year fixed effects. Cluster-robust standard errors at the bank level are reported in parentheses. The reference year is 2010. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Appendix G - Correlation Matrix

Variables	*ROA*	*ROE*	*NIM*	*RECExposure*	*HHI*	*Size*	*Capital_Ratio*	*Cost_Income*	*Credit_Risk*	*Deposit_Ratio*	*Mortgage_sh*
ROA	1.000										
ROE	0.716	1.000									
NIM	0.354	0.357	1.000								
RECExposure	-0.014	0.015	-0.241	1.000							
HHI	-0.002	0.120	0.018	0.164	1.000						
Size	0.177	0.058	-0.170	0.020	-0.340	1.000					
Capital_Ratio	-0.136	0.004	-0.046	0.247	-0.581	1.000	1.000				
Cost_Income	-0.630	-0.622	-0.329	0.122	-0.040	-0.292	0.168	1.000			
Credit_Risk	-0.287	-0.367	0.104	-0.131	0.047	0.037	-0.127	-0.006	1.000		
Deposit_Ratio	0.032	-0.097	-0.329	0.033	-0.286	0.084	0.183	0.211	-0.125	1.000	
Mortgage_sh	-0.005	-0.091	-0.397	0.037	-0.477	0.672	-0.228	0.003	-0.048	0.433	1.000

Notes: This table reports the correlation coefficients between the main variables used in the empirical analysis. Correlation coefficients are computed using bank-year observations from Banco de Portugal (BPLIM). The results do not indicate the presence of severe multicollinearity among the explanatory variables.

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