Profitability and Efficiency of the UK Commercial Banks Over Periods of Unstable Markets: 2010-2021

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Copyright Statement

Abstract

The thesis has been directed to empirically investigate the financial performance (profitability and efficiency) of the UK commercial banks using an unbalanced panel dataset covering 416 bank-year observations of 38 domestic and foreign commercial banks operating in the UK from 2010 to 2021. This period reflects numerous financial, political, and economic decisions and events, such as the post-2007/09 global financial crisis, the Basel Capital Accord (Basel III), Brexit, and the Covid-19 pandemic. As financial institutions are sensitive to such events, the financial performance (profitability and efficiency) of the UK banking sector is subjected to be affected by these events. The banking sector faces various challenges in dealing with the urgent requirements of this contemporaneous system. These challenges force banks' management to put extra effort into managing their financial activities to improve their profitability and efficiency, increasing stakeholder wealth. In line with other fundamental businesses, the banking sector is recognised as building the country's economy and guaranteeing stability for that economy. To this end, efficient financial performance requires UK commercial banks' managers, supervisors, and financial policymakers to know and understand the determinants of performance measures (profitability and efficiency). This research investigates the association between UK commercial banks' profitability and presumed bank-specific (internal), industry-specific, and macroeconomic (external) explanatory variables. Also, the efficiency of UK commercial banks is evaluated using two stages. In the first stage, the Data Envelopment Analysis (DEA) double bootstrap method was applied to examine bank efficiency scores, providing a comprehensive explanation and comparison of efficiency between different bank groups based on the size, ownership status and ownership structure. In the second stage, regression models were used to investigate the determinants of banks' efficiency.

Also, for both performance measures, profitability and efficiency, the research period has been divided into two sub-periods (before and after 2016, the year of Brexit) to investigate the determinants of profitability and efficiency of the UK commercial banks. This research applies the methods of the Generalised Method of Moments (GMM, employing the system and difference estimators with both (one-step) and (two-step) procedures) to estimate the dynamic panel data models. The Ordinary Least Squares (OLS) and the Fixed Effect (FE) models are used for comparison. This research contributes to the existing literature by using a dataset covering the recent and the more extended period from 2010 to 2021. It considers additional factors, such as Basel III liquidity ratios, Brexit and Covid-19, not employed in previous studies of the UK banks' profitability and efficiency. This research provides the basis for developing in-depth knowledge of the UK commercial banks to improve their financial performance (profitability and efficiency) and efficient decision-making by UK commercial bank managers. It also helps policymakers with future decisions to balance market conditions for banks, which will contribute to overall economic stability.

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Declaration

I declare that whilst registered as a candidate for the university's research degree, I have not been a registered or enrolled doctoral candidate for any other award from the university or other academic or professional institution.

Signed: *Mu'ath Khalaif Al-Qaraleh*

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Abbreviations

1D	GMM Estimator Using One-Step Difference.
1S	GMM Estimator Using One-Step System Procedures.
2D	GMM Estimator Using Two-Step Difference.
2S	GMM Estimator Using Two-Step System Procedures.
AE	Allocative Efficiency.
AT1	Additional Tier 1 Capital.
AR1	Arellano and Bond Tests for First-Order Autocorrelation.
AR2	Arellano and Bond Tests for Second-Order Autocorrelation.
ATMs	Automated Teller Machines.
BCC	Banker, Charnes, and Cooper (1984) Model, Presenting the Variable Returns to Scale.
BCC-BC	Variable Return to Scale Bias-Corrected.
BOE	Bank of England.
BSA	Building Societies Association
BXT	Brexit.
CAR	Capital Adequacy Ratio.
CCR	Charnes, Cooper, and Rhodes (1978) Model, Presenting the Constant Return to Scale.
CCR-BC	Constant Return to Scale Bias-Corrected.
CET1	Common Equity Tier 1.
COV	Covid-19 Pandemic.
CRS	Constant Returns to Scale.
DEA	Data Envelopment Approach.
DEP	Deposits Ratio.
DFA	Distribution-Free Approach.
DMUs	Decision-Making Units.
EEA	European Economic Area.
ESA	European System of National and Regional Accounts.
ETR	Effective Tax Rate.
EU	European Union.
FCA	Financial Conduct Authority.
FE	Fixed-Effects.
FGR	Financing Gap Ratio.
FPC	Financial Policy Committee.
FSA	Financial Services Authority.
GDPG	Growth Rate of Gross Domestic Product.
GFC	Global Financial Crisis.
GMM	Generalised Method of Moments.
HBOS	Halifax and Bank of Scotland.
HMT	Her Majesty’s Treasury.
HSBC	Hongkong and Shanghai Banking Corporation.
INF	Inflation Rate.
IRR	Internal Rate of Return.
LCR	Liquidity Coverage Ratio.
LOAN	Loan Specialisation Ratio.
LOANGR	Loan Growth Ratio.

MC	Market Concentration Ratio.
MENA	Middle East and North Africa
MFI	Monetary Financial Institutions.
NIM	Net Interest Margin.
NPL	Non-performing Loan Ratio.
NSFR	Net Stable Funding Ratio.
OE	Operating Efficiency.
OECD	Organisation for Economic Co-operation and Development.
OEE	Overall Economic Efficiency.
OLS	Ordinary Least Squares.
OTE	Overall Technical Efficiency.
PCL	Provision for Credit Losses.
PRA	Prudent Regulatory Authority.
PVINM	Predicted Value of Net Interest Margin.
PVROA	Predicted Value of Return on Assets.
ROA	Return on Assets.
ROAA	Return on Average Assets.
ROAE	Return on Average Equity.
ROE	Return on Equity.
ROI	Return on Investment Ratio.
RWAs	Risk-Weighted Assets.
SFA	Stochastic Frontier Approach.
SIZE	Bank Size.
SSE	Squares Error.
TSB	Trustee Savings Bank.
TE	Technical Efficiency.
TFA	Thick Frontier Approach.
UK	United Kingdom.
US	United States of America.
VAT	Value-Added Tax Rate.
VRS	Variable Returns to Scale.

Chapter 1: Introduction

1.1 Research background, motivations, and contributions

With the turn of the 21st century, financial crises have become recurring events, causing recession and increasing uncertainty across many economies worldwide. During the last decade, the UK economy, as a linked and significant leading centre, has experienced challenging and unstable financial events, putting the whole economy and policymakers under the most challenging decisions to stabilise the financial system and overcome the unpredictable effects of the major global financial crisis 2007/09 (Mor, 2018). The crisis spread into the UK financial sector and the real economy, causing funding issues to facilitate economic activities before it led the UK into a recession. The events from the collapse of the US subprime market in 2007 required developed governments to execute bailouts/pass laws to support the financial system. Also, the efforts of central banks within the influenced nations devoured all their capabilities to restore confidence within the system. Their actions included cutting base rates, supplying liquidity into the system, and launching an exceptional quantitative easing programme. According to Mor (2018), the unsuccessful coordination with the EU and the continuing decline of the UK stock markets had led the UK government to begin a comprehensive bailout plan. A £500bn bailout package was announced in October 2008 to prevent the collapse of the banking sector. This initial plan included three pillars: i) recapitalisation, to be done through a Bank Recapitalisation Fund, for £50 bn; ii) a Credit Guarantee Scheme, through a government loan guarantee for new debt issued between UK banks, for £250bn; and iii) liquidity support, through short-term loans provided by a Special Liquidity Scheme, directed by the Bank of England, for up to £200bn.

The post-2007/09 financial crisis has been a period of reconciliation within the balance sheets of the UK financial sectors. There has been a considerable restructuring of UK institutions through selling assets, closing investment businesses, stricter lending rules and holding more capital. Following the intervention of the government and Bank of England, more stringent regulations have been implemented or are in the process of doing so, outlined by the proposals of the Turner Review in 2009. Further to the Turner Review, the UK government reformed the regulatory bodies, which paved the way for creating the Financial Conduct Authority (FCA) and the Prudential Regulation Authority (PRA) (Bank of England 2020c). The Vickers Report's outcome 2011 calls for the banking sector to hold additional capital and the ring-fencing to separate banking activities from investment activities. Additional measures were taken in 2010 by the government to create future financial stability, which established the independent banking commission to reform the sector further (Edmonds 2013). The suggested reforms have directly impacted the industry's business models. The proposed regulations also could negatively impact the economy's overall performance as this would restrict financing in specific financial sectors.

In 2010, the member states of the Group of Twenty (G-20)[1] officially endorsed Basel III, which aims to increase the quality and quantity of capital banks must hold. Alongside this development, the Basel Committee on Banking Supervision (BCBS) provided a comprehensive reassessment of risk coverage assumptions and guidelines (Mili et al. 2017). The regulatory model recommended by the BCBS is perceived as a prerequisite for the proper functioning of global banking systems. In this context, the capital adequacy ratio has received special attention from international regulatory authorities as it is one of the essential regulatory tools used to control and scrutinise a bank's financial health. Regulators see Basel III as an essential measure of depository institutions' safety and soundness. They consider capital as a safety margin capable of absorbing potential losses. Basel III breaks down Tier 1 capital into "Common Equity Tier 1" and "Additional Tier 1". The Common Equity Tier 1 must account for at least 4.5% of a bank's RWAs. The Additional Tier 1 capital must account for at least 1.5% of a bank's Risk Weighted Assets (RWAs). In addition, Tier 2 capital is arranged at 2.0% of a bank's RWAs, giving together a minimum of 8% total capital ratio (Mili et al. 2017).

Later, the BASEL III framework refined the capital adequacy ratio by increasing its minimum requirement from 8% to 10.5%. Following this act, the Basel III regulatory accord revised principles of liquidity risk management (2008), and two quantitative measures, the Liquidity Coverage Ratio (LCR) (2013) and the Net Stable Funding Ratio (NSFR) (2014), have been introduced to tackle the liquidity risk and improve its management (Mennawi and Ahmed, 2020). These new frameworks were sought to limit banks' investment options and risk strategies to resolve short- and long-term liquidity management issues. The measures are intended to boost banks' liquidity support and financial stability. The LCR seeks to ensure banks have enough liquidity to provide short-term, up to one month, coping with liquidity problems. The NSFR intends to guarantee that banks have adequate, stable assets to solve long-term liquidity problems for one year. NSFR addresses more fundamental changes in the asset-liability liquidity mismatch (Sidhu et al. 2022).

After six years of the endorsement of Basel III, the UK's economic and political environment was challenged by the country's decision to leave the European Union (Brexit). Brexit refers to the UK's exit process from the European Union, shaped by the 2016 referendum. The process of Brexit practically started in June 2016, when voters in the United Kingdom determined to leave the European Union. It is scheduled to end in October 2019 with the definitive withdrawal of the UK from the EU. Brexit immediately impacted the UK economy. Atkinson (2022) argues that Brexit has reduced the openness and competitiveness of the British economy. The referendum increased UK inflation by 1.7 percentage points in 2017, resulting in an annual cost of around £400 for the average British household (Sampson et al. 2020), with estimated economic costs of 2.5% of GDP (Savage and McKie 2018), and a decreased

[1] Group of Twenty is an intergovernmental forum comprising 19 countries and the European Union (EU), working to address major issues related to the global economy, such as international financial stability, climate change mitigation, and sustainable development.

in British national income by 0.6% and 1.3% (Giles 2017). The uncertainty around Brexit decreased investment by around six percentage points and caused a reduction in employment by 1.5 percentage points (Chen, Mizen and Bloom 2018). Portes and Forte (2017) reported a significant adverse effect on UK GDP per capita because of Brexit-induced reductions in migration.

After a few months of the definitive withdrawal from the EU, the UK economy has been hit again by the Covid-19 pandemic, putting the UK's economy and policymakers in challenging and unstable financial events. The crisis has caused a global collapse, inactivity and loss of jobs that were exceptional in scale and speed. The majority of the small and large businesses across every country globally have had to close their doors to customers and workers. The sharp decrease in businesses' revenues and households' incomes resulted in the first global recession, presenting the global financial system with the most significant stress event since the global financial crisis of 2007/09 (Demirgüç-Kunt, Pedraza and Ruiz-Ortega 2021). The Bank of England's response to the pandemic was clear and compelling. The BoE was performed to save jobs and support the UK economy through measures and determinations. In March 2020, the BoE cut its interest rate (Bank Rate). The cut in the Bank Rate offered the UK banks and building societies long-term funding at interest rates of 0.1% (Bank of England 2020a). This resulted in cheaper loans for businesses and households. This reduced the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households. Moreover, the UK banks decided not to pay dividends to their shareholders in 2020 (Bank of England 2020a).

With the global financial system's crisis, challenges, and competition, financial institutions have been driven to move from traditional activities to focus more on technological improvement, innovation, and globalisation. This helps them overcome the negative impact of the events mentioned earlier to sustain their financial performance and contribute to stabilising the country's economy. As financial institutions are sensitive to such events, the financial performance (profitability and efficiency) of the UK banking sector, among other sectors, is subjected to be affected by the Basel Capital Accord (Basel III), Brexit, and the Covid-19 pandemic. The banking sector faces various challenges in dealing with the urgent requirements of the contemporaneous financial system. These challenges force banks' management to put extra effort into managing their financial activities to improve their profitability and efficiency, increasing stakeholder wealth. In line with other fundamental businesses, the banking sector is recognised as building the country's economy and guaranteeing stability for that economy. To this end, efficient financial performance requires UK banks' management, supervisors, and financial policymakers to know and understand the determinants of performance measures.

The last updated Monetary Financial Institutions (MFI) listed by the Bank of England (2023) shows that the UK banking sector involves around 352 banks and building societies. In 2018, there were approximately 11,065 banks and building society branches, compared to 12,270 branches in 2008. The number of banks and building society branches per head of population is fairly spread across the UK, with an average of 1.7 branches per 10,000 people in each region and country of the UK. Moreover, 63,100 cash machines (9.2 ATMs per 10,000 residents), of which 52,000 out of the total were free to use (Rhodes 2020). Packman (2022) reported that the UK banking sector's estimated total tax contribution to the UK public finances was £38.8bn in 2021.

The motivation and contributions of performing this research are three-fold. First, the current research contributes to the literature by investigating the internal and external determinants of the UK banking sector's performance (profitability and efficiency) using the most up-to-date dataset from 2010 to 2021. This period starts with the post-global financial crisis of 2007/09, passing by Basel III and Brexit, and ends with the recent global pandemic, Covid-19. The global financial crisis of 2007/09 has had a lasting impact on the UK economy, and, in one form or another, it influenced the vast majority of the public. This event resulted in increased unemployment, reduced spending on public services due to bailouts from the government to the financial sector, or any other reason related to the crisis.

Second, this research is essential to understanding how the market has received incoming financial regulations. Whether boosted regulations were perceived to be positive, resulting in increased stability, enables more participants to the market. Contrarily, an adverse reaction from the market would suggest that the tightening of regulation would impact the financial sectors' business models and lower their risk and return. The current research uses the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) as Basel III ratios to estimate their impacts on the UK commercial bank's financial profitability and efficiency. The aim is to determine whether the LCR and NSFR capital requirements are optimal for achieving higher stability and sustaining profitability and efficiency.

Lastly, the current research contributes to the literature by investigating the impact of Brexit on banks' performance measures, profitability, and efficiency. This research provides empirical results and compares sub-periods (before and after 2016, the year of Brexit). Also, a dummy variable is used to capture the impact of Covid-19 on the UK commercial banks' profitability and efficiency. Brexit and the Covid-19 pandemic have negatively impacted the UK economy in challenging situations to make decisions to overcome their inverse impacts. It is critical to undertake such research for the general public and taxpayers to understand what happened within the financial sectors, mainly banks, which caused a recession in the UK, and how important the decisions and actions made by the government and Bank of England are. The proposed changes in the Vickers Report 2011 were supposed to produce financial stability as risky activities are solely held within the non-ring-fenced units. With a better understanding of this research, policymakers will be more informed when determinations are made regarding preserving the health of the UK banking sector as part of the financial system. By understanding the attributes of the more significant financial performance of the UK commercial banks,

banks' management can optimise their performance (profitability and efficiency) and benefit the economy.

The literature across the UK banking sector needs to be updated. It is vital to consider an irregular period (2010-2021) covering the post-2007/09 global financial crisis, new financial regulations (Basel III), Brexit, and the most recent crisis of Covid-19. It is reasonable to assume that those mentioned economic and political events significantly challenge UK commercial banks, affecting their financial performance. Consequently, this gives additional motivation to conduct new research in this matter, create a debate within the current strand of literature, contribute to knowledge within the field of finance, and provide more comprehensive, reliable results of UK commercial banks' performance that could benefit the banks' management and the UK financial policymakers.

1.2 The theory of financial intermediation

The theory of financial intermediation is a framework used in economics and finance to understand the role of financial intermediaries in the financial system. Financial intermediaries stand between savers and borrowers, facilitating the flow of funds from those with a surplus (savers) to those who need funds (borrowers). This theory helps explain how financial markets operate and how intermediaries contribute to efficient capital allocation (Allen and Santomero, 1998). The theory explains how intermediaries help overcome information asymmetry, manage risk, and efficiently allocate funds between savers and borrowers. These intermediaries are vital for the functioning of modern financial markets and contribute to the stability and growth of the economy.

The financial intermediation theory of banking is a specific aspect of the broader theory of financial intermediation, focusing on the role of banks as critical financial intermediaries in the economy. This theory emphasises banks' unique functions and activities within the financial system. Allen and Santomero (2001) summarise the fundamental principles and concepts of the financial intermediation banking theory as follows.

- Depository Function: Banks serve as depository institutions where individuals and businesses can deposit surplus funds. These funds are held in various accounts, such as checking accounts, savings accounts, and certificates of deposit (CDs). This function allows savers to earn interest on their deposits while maintaining liquidity.

- Lending Function: Banks channel the deposited funds into various forms of lending, including commercial loans, consumer loans, and mortgages. Banks provide borrowers the required capital to finance their investments, business operations, or personal expenses through this lending activity.

- Credit Intermediation: Banks assess the creditworthiness of potential borrowers and allocate funds to those who meet their lending criteria. This intermediation role involves analysing credit risk, setting interest rates, and monitoring borrowers to ensure repayment.

- Maturity Transformation: One of the fundamental functions of banks is maturity transformation. Banks take short-term deposits from savers and use these funds to make long-term loans. This process allows banks to match the varying maturity preferences of savers and borrowers, earning a spread (the difference between the interest paid on deposits and earned on loans).

- Risk Management: Banks play a crucial role in risk management. They diversify their loan portfolios across different sectors and borrowers to reduce risk. Additionally, banks often require collateral and impose covenants to mitigate credit risk.

- Payment System: Banks provide a secure and efficient payment system that enables individuals and businesses to make transactions. This includes check clearing, electronic funds transfers, and credit and debit card processing.

- Liquidity Provision: Banks offer liquidity to depositors, allowing them to withdraw their funds on demand. While banks may have illiquid assets (such as long-term loans), they ensure that depositors can access their money when needed.

- Interbank Transactions: Banks engage in interbank transactions to manage their liquidity needs and maintain the financial system's stability. They lend to and borrow from other banks in the interbank market.

- Role in Monetary Policy: Central banks often use commercial banks as intermediaries to implement monetary policy. They may influence the money supply by adjusting interest rates or reserve requirements for banks.

- Regulation and Supervision: Due to banks' vital role in the economy, they are subject to strict regulatory oversight to ensure their safety and soundness. Regulations also aim to protect the interests of depositors and maintain financial stability.

The financial intermediation theory of banking highlights banks' essential role as intermediaries in the financial system. They facilitate the flow of funds between savers and borrowers, provide liquidity, manage risk, and contribute to the overall stability and functioning of the economy. This theory helps explain why banks are a cornerstone of modern financial systems and are subject to significant regulation and supervision.

1.3 Research objectives

Since the objective is to examine the performance (profitability and efficiency) of the UK banking sector over a crisis-related period (2010-2021), this research aims to contribute to the literature on banking performance, explaining the factors that affect the UK commercial bank's profitability and efficiency. The first objective is to find the internal (bank-specific) and external (industry-specific and macroeconomics) determinants of UK commercial banks' profitability over the research period and before and after the year of Brexit (2016) by analysing the data of the subsamples (pre and post-Brexit). To this end, this research will be conducted by utilising a panel data regression methodology in the framework of a dynamic panel model that is in line with Berger et al. (2000), Goddard, Molyneux and Wilson (2004), and Athanasoglou, Brissimis and Delis (2008). These empirical studies assume that banks' profits tend to persist over time. They identify an endogeneity problem when observations of the explanatory variables are not entirely independent of past values of the dependent variable. Accordingly, they included banks' profitability as a lagged variable among the regressors. This methodology enables accounting for heteroskedasticity and resolves any limited data issues that may arise when conducting this research. The dynamic Generalised Method of Moments (GMM) model widely exists among researchers who directed their studies using panel data. The model was presented in 1991 by Manuel Arellano and Stephen to address specific endogeneity problems. According to Baltagi (2021), the Arellano–Bond estimator is a generalised method of moments estimator used to gauge dynamic panel data models.

Secondly, this research also aims to identify the internal (bank-specific) and external (industry-specific and macroeconomics) determinants of UK commercial banks' efficiency by applying an advanced semi-parametric two-stage method introduced by Simar and Wilson (2007). In the first stage, the Data Envelopment Analysis (DEA) will be adopted to estimate the sample's relative efficiency scores using Constant Returns to Scale CRS (CCR model) and Variable Returns to Scale VRS (BCC model). The second data analysis stage will apply the Simar and Wilson (2007) procedure to bootstrap the DEA scores.

To understand to what extent the UK commercial banks' characteristics affect their overall technical efficiency, banks for the first analysis stage in this research will be classified into three groups based on their characteristics (size, ownership structure, and ownership status) to compare between UK commercial banks based on the estimated efficiency scores, presenting the average scores for the initial technical efficiency and the technical efficiency as the double bootstrap method. Lastly, this research aims to provide policy implications for UK financial policymakers, bankers, and investors.

1.4 The structure of the thesis

Chapter 2 presents a background of the UK banking sector. The chapter starts with a brief description of the UK financial system before introducing the UK banking sector. This chapter overviews the monetary financial institutions, including the central bank, UK banks, and UK building societies. The chapter also presents the UK financial regulators, covering the Bank of England (BoE), the Financial Policy Committee (FPC), the Financial Conduct Authority (FCA), the Prudential Regulation Authority (PRA) and Her Majesty's Treasury (HM Treasury). Lastly, the chapter focuses on recent financial, political, and economic events, such as the global financial crisis of 2007/09 and the UK government's responses to its effects, Basel III, Brexit, and the Covid-19 pandemic.

Chapter 3 reviews the related literature on bank profitability and its determinants. The chapter introduces the concept of profitability to give the reader a better understanding of the "profitability" concept before moving to the rest of the chapter. Then, the chapter comprehensively explains profitability from a firm's perspective and how it is considered a financial performance indicator. Furthermore, the section on profitability measurement explains how profitability is measured by presenting the most used financial ratios by giving brief information about each ratio and how it is calculated. Lastly, the chapter discusses the literature on bank profitability by addressing the studies conducted on this topic. It detailed the regions, data samples, variables, and the results of these investigations. In addition to reviewing bank profitability literature, a brief review of the relevant studies in the following chapters is also provided.

Chapter 4 explains the methodology and method of investigating the determinants of UK banks' profitability. The chapter is organised into sections presenting the research questions and the research hypothesis. Then, it presents the research philosophy and approach, followed by the data type and collection method. Furthermore, it presents the research period, sample, and data. It also provides a detailed explanation of the determinants of bank profitability and variable selection. This section has two sub-sections, presenting the profitability measures (dependent variables) and the bank-specific, industry-specific, and macroeconomic factors (independent variables). The Ordinary Least Squares (OLS) and Fixed Effects (FE) are presented in the section on standard estimators. The chapter also presents the econometric specification of the dynamic panel system Generalised Method of Moments (GMM) model used for analysing the data. Lastly, it presents the data analysis method.

Chapter 5 is dedicated to empirical data analysis of UK bank profitability. Thirty econometric models (one model of OLS, FE, and four GMM models for each proxy of profitability) are used to investigate the association between the UK banks' profitability (Return on assets, return on average assets, return on equity, return on average equity, and net interest margin as proxied by ROA, ROAA, ROE, ROAE and NIM, respectively) and the presumed internal and external explanatory variables. The chapter illustrates the econometric results of the regression analysis using the OLS, FE, and GMM models. It presents the descriptive statistics for the variables used in the regression analysis, then the correlation matrix and the test for multicollinearity. Moreover, it presents the models and steps for the estimation process. Lastly, the chapter provides a comprehensive discussion of the regression analysis results.

Chapter 6 reviews the related literature on bank efficiency and its determinants. The chapter introduces the concept of efficiency and its drivers. Doing so gives the reader a better understanding of the concept before moving to the rest of the chapter. It explains the efficiency types, including scale efficiency, X-efficiency, technical efficiency, pure technical efficiency, allocative efficiency, and other types, such as cost efficiency and scope efficiency. The chapter comprehensively explains the structural, non-structural, traditional, parametric, and non-parametric banking efficiency measures. Lastly, the chapter discusses the existing literature on bank efficiency by addressing the studies conducted on this topic. It shows the regions, data samples, models for analysis, input and output variables, and the results of these studies in detail. Also, a summary of some recent studies on bank efficiency is presented.

Chapter 7 presents and explains the methodology for investigating efficiency and its determinants in the UK banking sector. The chapter is organised into sections, which present the research questions and the research hypothesis. Also, it presents the research philosophy and approach, the data type, and the collection method. Moreover, it discusses the CCR and BCC models, the bootstrap two-stage procedure, the first-stage DEA efficiency estimate, and the second-stage regression. The chapter also explains the specification of the inputs and outputs and the specification of the dependent and independent variables used for the data analysis. The chapter includes three primary tables presenting valuable information regarding CCR and BCC models, definitions and descriptions of the selected input and output variables for the first stage of the analysis, and descriptions and the expected effect of the variables for the second stage. These variables are classified into bank-specific, industry-specific, and macroeconomic factors.

Chapter 8 demonstrates the results of investigating the efficiency of the UK banking sector. For the first stage analysis, relevant environment-independent inputs and outputs are specified for the DEA analysis within this research method. These inputs and outputs are first performed to compute the relevant efficiency scores for the analysis considering the overall technical efficiency (CCR) and pure technical efficiency (BCC) by solving the proper DEA models. The estimated efficiency scores from this stage are used as dependent variables for the second data analysis stage. For the second stage, twelve econometric models (one model of OLS and FE and four GMM models for each proxy of efficiency) are used to examine the relationship between the UK banks' efficiency (overall technical efficiency and pure technical efficiency as proxied by RCC-BC and BCC-BC) and the presumed environmental explanatory variables.

Chapter 9 summarises the main results of the research conducted as outlined above. The literature is enhanced by filling a gap in UK banks' financial performance (profitability and efficiency) over unstable market conditions during 2010- 2021. The thesis points to policy implications for many respective UK bodies due to the depth and scope of the research conducted. The chapter outlines issues within the research for policymakers to regard when adopting new regulations and financial and regulation strategies. Also, the chapter presents the recognised limitations and other challenges throughout the empirical chapters. Lastly, the chapter draws directions where the research can be furthered in future works based on the limitations and challenges faced while conducting the present research.

Chapter 2: Background of the UK Financial Sector

2.1 Introduction

The UK banking system has experienced a notable change over the last three decades. This period has been characterised by the volatility of prosperity and failure from the early 1990s, passing by the global financial crisis of 2007/09 to the most recent crisis of the Covid-19 pandemic. The sector grew increasingly through the actions of mergers between large and small-sized banks. The domain of banks' activities changed by shifting from the traditional model of lending and deposit-taking to a new model of trading and wholesale funding.

Regulations have changed significantly, both domestically and internationally. The international structure moved from the initial Basel I agreement, which focused mainly on establishing capital requirements for credit risk, to Basel II, authorising more widespread use of internal models for setting capital requirements. Domestically, regulations were developed in forms unique to the UK, with bank-specific supervisory add-ons to capital and liquidity requirements that can help overcome classification challenges for causal inference (De-Ramon, Francis and Milonas 2017).

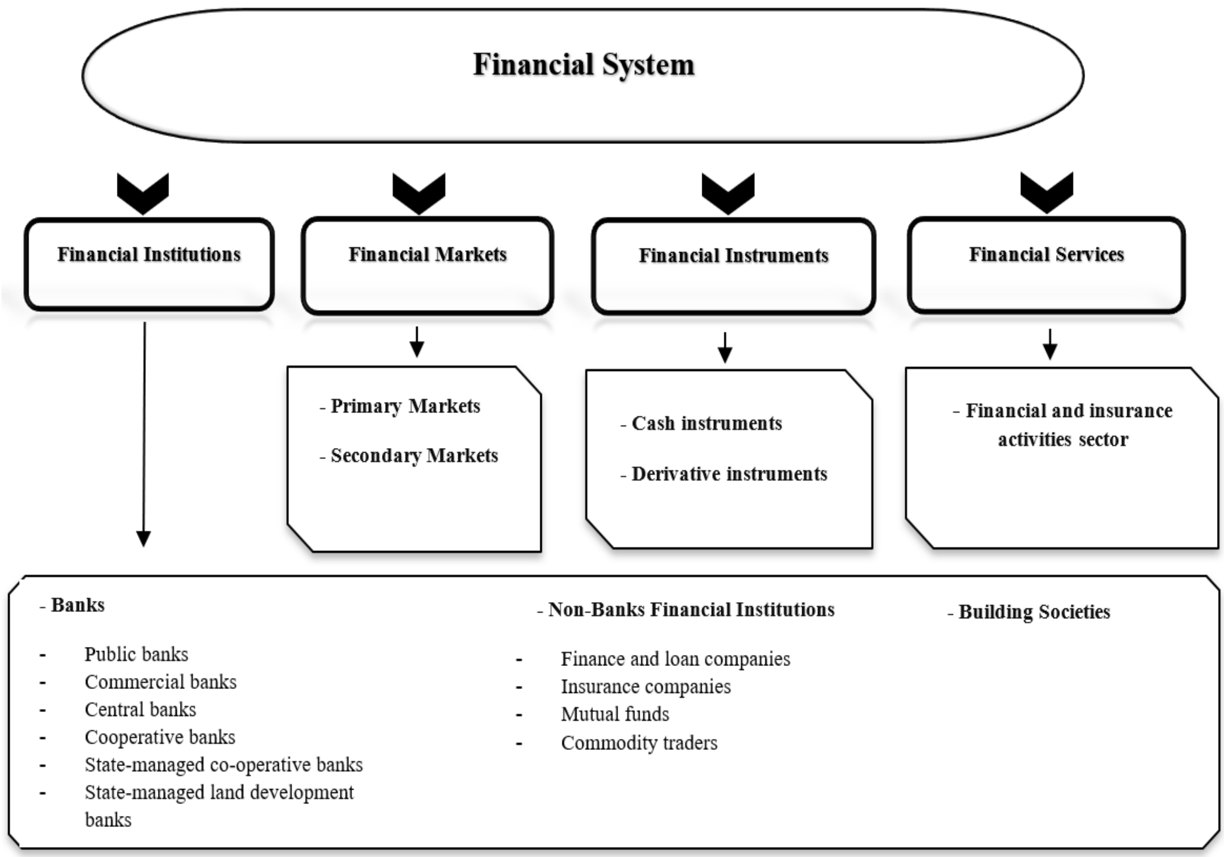
As part of the financial system, the banking sector faces various challenges in dealing with urgent and contemporary requirements that regulate and control the sector's activities. These challenges force banks' management to put extra effort into managing their financial activities to reach the crucial goal: improving their profitability and efficiency, increasing stakeholder wealth, and contributing to the stability of the country's economy. In line with other fundamental businesses, the banking sector is recognised as building the country's economy and guaranteeing stability for that economy. Payment services, intermediation between lenders and borrowers, and insurance against risk are the three essential services the banking sector provides to sustain capital allocation and exchange the produced goods and services: a well-functioning economy. However, these financial services cannot be relatively timeless due to the ongoing changes in the system's characteristics that provide them because of economic and regulatory developments.

This chapter gives an overview of the UK financial system with a focus on the banking sector during the research period of 2010-2021. The chapter is organised as follows. Section 2.2 briefly describes the UK financial system. Section 2.3 describes and classifies the UK monetary financial institutions. Section 2.4 presents the UK financial regulators, providing a discussion on the roles of the Bank of England (BoE), the Financial Policy Committee (FPC), the Financial Conduct Authority (FCA), the Prudential Regulation Authority (PRA), and Her Majesty's Treasury (HM Treasury). In Section 2.5, some recent financial and economic events are discussed. These events included the 2007/09 global financial crisis, summarising its stages in the UK, and the rescue packages and the schemes that were taken to overcome its adverse impacts on some UK banks in response to the crisis. Also, the section discusses the introduction of the Basel Capital Accord (Basel III), highlighting the required capital banks must hold as a response to the 2007/09 global financial crisis. The section overviews the UK's departure from the EU (Brexit). The section also sheds light on the most recent global event (Covid-19) by briefly discussing the pandemic's effect on the UK economy and the Bank of England's actions to absorb its economic effects. Lastly, a summary of the chapter is given in Section 2.6.

2.2 Brief description of the UK financial sector

A financial system can be defined at a global, international, regional, or business level. It commonly refers to a system that facilitates transferring money between parties, mostly surplus units (investors and lenders) and deficit units (borrowers). The essential components of the financial system are financial institutions, financial markets, financial instruments (assets or securities), and financial services. An illustration of these components is presented in Figure 2.1.

Figure 2.1: Components of a financial system.



Source: Adapted from Burrows and Low (2015).

A well-functioning financial system may have positive spill-over effects for other sectors of the economy. For example, it may enhance businesses' credit access and help other sectors grow. According to Yeandle and Mainelli (2022), the Global Financial Centre Index 32 shows that the UK financial sector is ranked the biggest in Europe and the second biggest globally, seven points back of New York.

The ranking is an aggregate of indices from five key areas: business environment, financial sector development, infrastructure, human capital, reputation, and general factors.

According to Hutton (2022), the UK financial services sector was the fourth largest in the Organisation for Economic Co-operation and Development (OECD) in 2021 based on its proportion of national economic output. In 2021, the sector was the largest in London, generating around half of the sector's output. The sector contributed 8.3% of the UK's total economic output, equal to £173.6bn to the economy. A 1.08 million financial services jobs (3.0% of all jobs in the UK) have been reported in Q1 2022. Moreover, exports of UK financial services were worth £61.3bn in 2021, and imports were worth £16.6bn, showing a surplus in the financial services trade of £44.7bn.

2.3 Classification and description of the UK monetary financial institutions

Based on the classification of accounts guide presented by the Bank of England (2018a), the UK monetary financial institutions are classified as follows.

2.3.1 Central Bank-Bank of England (BoE)

The European System of National and Regional Accounts defines the Central Bank as a separate sub-sector within total Monetary Financial Institutions. Unlike other kinds of banks, the central bank is not market-based and does not directly deal with the public. Instead, it controls inflation and monetary policy, maintains currency stability, and supervises the country's money supply. Further, the central bank regulates member banks' capital and reserve requirements. In the UK, the BoE is the central bank and includes the Banking Department, the Issue Department, and the Asset Purchase Facility of the Bank of England.

2.3.2 Monetary financial institutions other than the Central Bank

It involves the UK financial sector institutions, whose activities are mainly performed in financial intermediation. Their business is to receive deposits and, for their private accounts, to offer loans and make investments in all kinds of securities. This classification includes:

2.3.2.1 UK banks

The term "UK banks" refers to all UK offices of banks approved to conduct deposit-taking in the UK. This classification involves the following sub-categories: i) Institutions with Part IV permission under the Financial Services and Markets Act 2000[2] to accept deposits, excluding credit unions, friendly societies, building societies, and companies with permission to accept deposits to continue insurance

[2] An Act to make provisions about the regulation of financial services and markets. It is designed to transfer specific statutory functions relating to building societies, friendly societies, industrial and provident societies and certain other mutual societies; and for connected purposes. More details on Part IV permission are available at: https://www.legislation.gov.uk/ukpga/2000/8/part/IV/enacted.

business purposes. ii) The European Economic Area (EEA) credit institutions with permission under Schedule 3 of the Financial Services and Markets Act 2000[3] to receive deposits through a UK branch. The two sub-categories exclude the Channel Islands and the Isle of Man institutions. Also, all banks authorised in the EEA are allowed to establish branches in the UK but do not receive deposits in the UK (Bank of England 2020b). The UK banking sector split as follows.

- The big five: Along with mutual, a small group of retail banks leads the High Street in the UK[4]. These banks are HSBC, Barclays Bank, Lloyds Bank Group[5], NatWest Group[6], and the UK subsidiary of Santander.

- Larger Challengers: The Larger Challengers refer to the longer instituted banks, typically more than ten years. Paragon, Williams & Glyn, Virgin Money[7], TSB, and First Direct are examples of Larger Challengers. Nationwide is one of the biggest mortgage providers in the UK, but it considers itself a Challenger regarding current accounts.

- Smaller Challengers: The Smaller Challengers have typically been united within the past five to ten years. Secure Trust Bank, OneSavings, Aldermore, Shawbrook, Charter Saving, Metro, Aldermore, and Close Brothers are Smaller Challengers banks. These banks were financed by private equity through their initial growth phase. Five of them are listed banks.

- Digitally focused challengers: The Digitally Focused Challengers refer to the most recent additions to the Challenger landscape. Each of them offers the promise of personalisation and technology as fundamental differentiators. The Digitally Focused Challengers also propose to partner with other institutions, and some have even practised customer crowdfunding to facilitate their expansion. Atom, Fidor Bank, Mondo, Starling, and Tandem are an example of Digitally Focused Challengers.

- Larger Retailers: Some large existing retailers such as Sainsbury's, Tesco, and Asda have joined the financial services market by offering savings accounts and unsecured products. Tesco has extended its offering with products such as mortgages and current accounts, hence more challenging the big banks.

The last updated Monetary Financial Institutions (MFI) listed by the Bank of England (2023) shows that the UK banking sector involves around 352 banks and building societies. In 2018, there were approximately 11,065 banks and building society branches, compared to 12,270 branches in 2008. The number of banks and building society branches per head of population is fairly spread across the UK, with an average of 1.7 branches per 10,000 people in each region and country of the UK. Moreover,

[3] Schedule 3 presents the EEA Passport Rights and all amendments to the Financial Services and Markets Act 2000. More details on permission under Schedule 3 are available at: https://www.legislation.gov.uk/ukpga/2000/8/schedule/3.
[4] Since the acquisition of Halifax and Bank of Scotland (HBOS) by Lloyds, the literature refers to the "Big Four" banks (HSBC Holdings Plc, Barclays Bank Plc, Lloyds Bank Group Plc, NatWest Group Plc).
[5] It was Lloyds TSB.
[6] Up to 2020, NatWest Group plc was known as The Royal Bank of Scotland Group (RBS Group).
[7] Virgin Money UK plc was formerly known as CYBG plc. The company's brands are Clydesdale Bank, Yorkshire Bank, and Virgin Money.

63,100 cash machines (9.2 ATMs per 10,000 residents), of which 52,000 out of the total were free to use (Rhodes 2020). Packman (2022) reported that the UK banking sector's estimated total tax contribution to the UK public finances was £38.8bn in 2021. The data collected for this research found that the "Big Four" UK banks hold £5.25tn, £2.74tn, and £1.91tn in terms of total assets, customer deposits, and net loans in 2021 compared to £5.50tn, £1.94tn, and £2.14tn in 2010, respectively. According to the concentration ratio, which indicates the degree of competition in an industry, the data also shows that the UK banking sector is dominated by a few exceptionally large banks (Big Four), stand at a market share of 57.65% of the UK banking sector's total assets in 2021 compared to 53.59% in 2010. This clearly shows that the market is oligopolistic.

2.3.2.2 UK building societies

Building societies are a type of financial institution that provides its members with banking and other financial services. They are like credit unions in which they are owned wholly by their members. They offer many traditional banking products and financial services such as mortgage lending, savings, and current accounts. According to the Building Societies Association (BSA) (2023), alongside seven credit unions in operation, there are 43 building societies working in the UK, providing their financial services through around 1,288 branches around the UK, with total assets of £483.18bn at the end of 2021. The most prominent building society in the UK, as reported by the Bank of England (2021), is Nationwide, with group assets worth around £255bn in 2021.

2.4 The UK financial regulators

At international or domestic levels, regulators and governors share their monitoring and regulatory activities between two domains: the banking and the financial markets. All nations are also developing suitable structures to guarantee the continuous functioning of markets in financial instruments. These arrangements collaborate globally. The intention of regulators also involves a critical amount of investigation, gathering information on the economy and the markets, and reflection while seeking a non-profit goal. Historically and yet, central banks worldwide take the "Banks of the banks" posture as lenders of last resort, besides being the state's bankers. The primary remit for most central banks is to maintain price stability, which means they are responsible for controlling inflation, which they can do by adjusting the supply of funds to the banking system.

The financial regulations in the UK have been going through changes since the late 1990s. In 1997, the Bank of England was stripped of its regulatory powers when it was granted independence. From that action up to 2013, the Financial Services Authority (FSA) was responsible for banking supervision (Bank of England 2020c). The FSA was an independent non-governmental body; it was a limited company financed by levies in the industry. The FSA was accountable to the Treasury. As a result, no single body oversaw the entire system. There were gaps between the so-called tripartite authorities, the

Bank of England, the FSA, and the Treasury. These gaps became apparent in the significant financial crisis of 2007.

The FSA had four main objectives: First, to maintain confidence in the UK financial system. Second, to promote public understanding of the financial system. Third, to secure appropriate protection for customers while recognising their responsibilities, and lastly, to reduce the scope of financial crime. Following the financial crisis, the Bank of England had its regulatory powers reinstated. The new structure came into operation on the 1st of April 2013. In addition to regulatory responsibility shifting back to the Bank of England, three new bodies were set up: The Financial Policy Committee (FPC), the Prudent Regulatory Authority (PRA), and the Financial Conduct Authority (FCA). The FPC's role is to oversee the financial stability of the financial system. The PRA is a subsidiary of the Bank of England and undertakes prudential regulation. The FCA's role is to monitor business conduct for systemic firms and consumer protection issues.

2.4.1 Bank of England (BoE)

The BoE is the UK's central Bank and the world's eighth-oldest bank. BoE was founded in 1694 to function as the banker of the English government and is still one of the bankers for the UK government. The Bank was nationalised in 1946 after being privately held by its stockholders since its establishment. In 1997, the BOE was given operational independence to set interest rates. This was set out in the Bank of England Act 1998. The government owns the Bank, with the bank's capital being held by the treasury solicitor on behalf of the Treasury.

The Bank is responsible for several functions. One of its primary roles is to guard the value of money by keeping prices stable. It is responsible for maintaining inflation close to the government's target of 2% + or - 1%. The consumer price index measures this. To this end, the BoE, through its monetary policy process, controls that by setting the core interest rate at which it lends to the banks and by buying or selling assets. It is also responsible for ensuring banks in the UK operate well. It achieves this through the Prudential Regulation Authority (PRA), which regulates and supervises banks, building societies and insurers. Moreover, it keeps the whole UK financial system stable through the Financial Policy Committee (FPC). The FPC's responsibility is to identify and monitor risks in the UK financial system and take actions to decrease or remove them when and where necessary (Bank of England 2020c).

2.4.2 Financial Policy Committee (FPC)

The 2007/09 financial crisis triggered realising the importance of financial stability. Therefore, policymakers recognised that more than focusing independently on price stability and supervising individual firms were required. To fill that gap, FPC was created by the UK Parliament through the (Financial Services Act 2012) to control risks and weaknesses across the financial system, mainly by identifying, monitoring, and acting against risks that threaten the resilience of the UK financial system.

It also helps the government's economic policy, including its goals for economic growth and jobs. The FPC consists of 13 mixed internal and external members; some work for the Bank of England, while others represent businesspeople and academics, providing a wide range of skills and experience for helping a better understanding of the risks and finding practical solutions.

The FPC has two central powers of directions and recommendations. Its directions are obligatory instructions provided to the Financial Conduct Authority (FCA) and the Prudential Regulation Authority (PRA), which were founded in 2013 in the wake of the previous regulator, the Financial Services Authority (FSA). The directions issued to the PRA to make banks, building societies, and significant investment businesses conduct specific actions. Regarding banks, this involves the power to set capital requirements for holding more money and the level for countercyclical capital buffers, which is the amount of money held in reserve. This helps banks with the need for enough capital and provides a solid basis for lending in case things go wrong. The FPC also makes recommendations on a 'comply or explain' basis to the FCA and the PRA. On this basis, the regulators must explain their reasons publicly if it is decided not to implement a comply-or-explain recommendation by the FPC (Bank of England 2020c).

2.4.3 The Financial Conduct Authority (FCA)

The FCA is the conduct regulator for 59,000 financial services institutions and markets in the UK, performing as the prudential regulator for more than 18,000 of these institutions. Moreover, these financial services institutions employ more than 2.2 million people and contribute around £65.6bn in tax to the country's economy (The Financial Conduct Authority 2019). The FCA's primary role is to ensure that the relevant markets function well to benefit customers, staff, and shareholders competitively and fairly and maintain confidence in the UK as a major global financial centre. It reaches that goal through its operational objectives: Consumer protection by securing a proper degree of protection for customers, Financial Markets Protection through protecting and enhancing the integrity of the UK financial system, and Promoting competition by promoting effective competition in the interests of consumers.

2.4.4 The Prudential Regulation Authority (PRA)

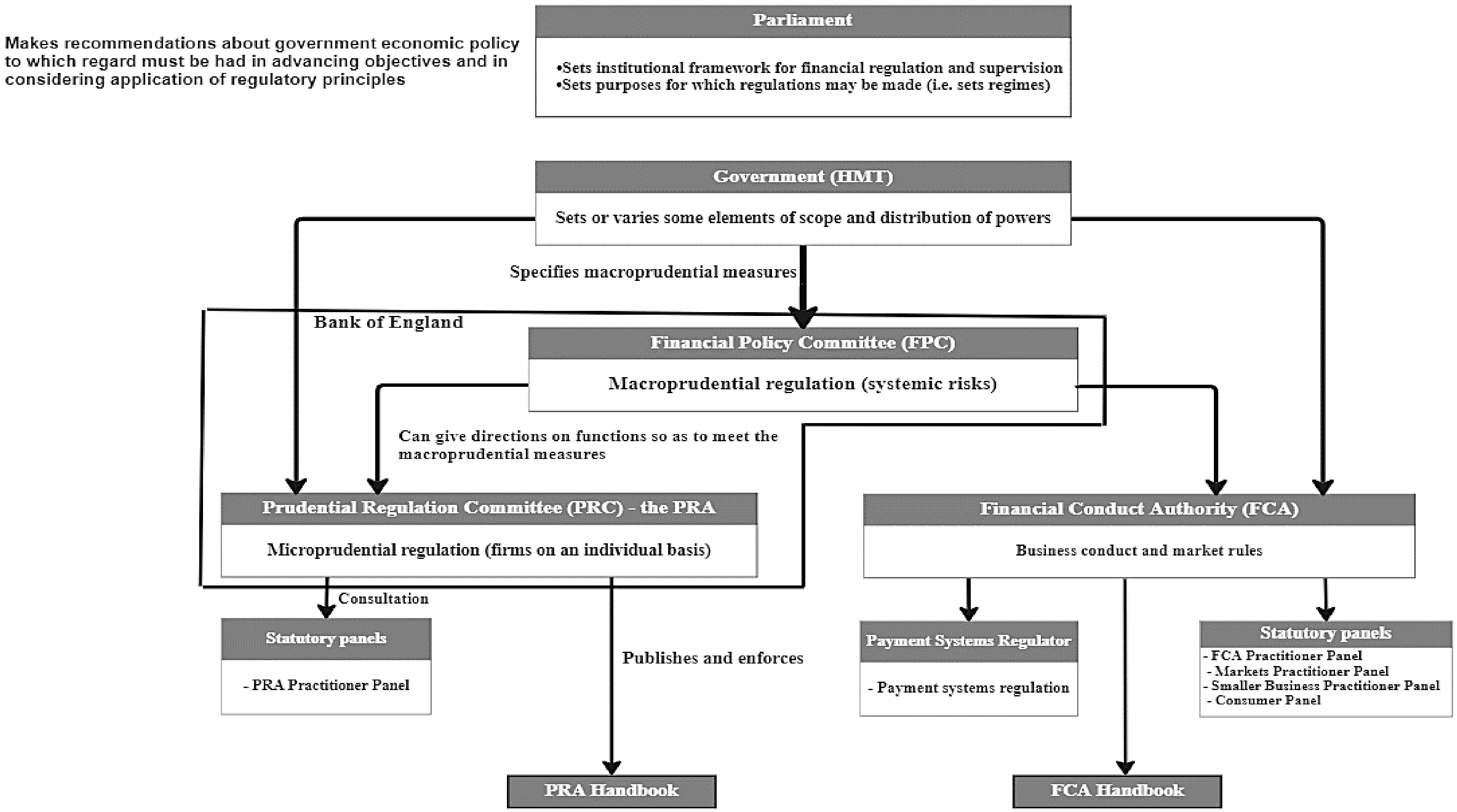
The PRA was established in line with the FCA as part of a new wave of regulation in the UK financial services after the global financial crisis of 2007/09. It is constructed as a limited company held by the Bank of England. PRA supervises over 1,500 financial institutions, including banks, building societies, credit unions, insurers, and significant investment firms (Bank of England 2018b).

The function of PRA is represented in terms of two legal purposes: First, promoting the safety and soundness of the firms it regulates by focusing fundamentally on the harm that financial institutions can cause to the stability of the UK financial system as a stable financial system guarantees firms to continue providing critical financial services, a precondition for a healthy and prosperous economy. Second, it contributes to securing suitable protection for policyholders, particularly insurers. PRA's regulation and supervision approach has three attributes: i) a judgement-based approach by using judgment in determining whether financial institutions are safe, whether insurers present suitable protection for policyholders, and whether organisations continue to meet the threshold conditions. ii) a forward-looking approach by assessing institutions not only against prevailing risks but also against those that could, in all probability, occur in the future. iii) a focused approach, focusing on issues and institutions that could pose a considerable risk to the policyholders and stability of the UK financial system (Bank of England 2018b).

2.4.5 Her Majesty's Treasury (HM Treasury)

HM Treasury is the UK government's economic and finance ministry. Its role is to maintain control over public spending and set the direction of the UK's economic policy to achieve healthy and sustainable economic growth. The HM Treasury's essential goals are: i) to set the public finances on a sustainable basis by securing value for money and improving outcomes in public services. ii) to guarantee the stability of the macro-economic environment and financial system and to enable sound, sustainable and balanced growth. iii) to enhance employment and productivity and ensure healthy growth and competitiveness across the UK through a comprehensive package of structural reforms. Lastly, strengthening a great Treasury by building a more inclusive and diverse department supported by professionalism, skills, and supervision excellence (HM Treasury 2019). An architecture for financial regulation and supervision in the UK is presented in Figure 2.2

Figure 2.2: The architecture for the financial regulation and supervision in the UK.



Source: Adapted from Adams, Fergusson and Hoban (2017, p. 18).

2.5 Financial, political, and economic events

2.5.1 The 2007/09 Global Financial Crisis (GFC)

A financial crisis may have various causes. Generally, a crisis can occur when institutions or assets are overvalued and can be worsened by irrational or herd-like investor behaviour. Pilbeam (2001) outlines three stages of a financial crisis that occur as follows.

The first stage is the initiation of the financial crisis. This stage can begin in several ways, such as mismanagement of financial liberalisation or innovation, asset price booms and busts or a general increase in uncertainty caused by the failure of critical financial institutions. Stage two is when deteriorating balance sheets and more challenging business conditions lead some financial institutions into insolvency when net worth becomes negative, and they are unable to pay off depositors or other creditors; some banks may go out of business if severe enough, these factors can lead to a bank panic, in which multiple banks fail simultaneously. If, however, the economic downturn leads to a sharp decline in prices, the recovery process can be short-circuited. If this occurs, an economic recovery will not be seen; stage three will appear. In stage three, debt deflation occurs in which a substantial unanticipated decline in the price level sets in, leading to a further deterioration in the firm's net worth because of the increased burden of indebtedness.

The 2007/09 GFC was the worst economic disaster since the Great Depression 1929 (Hausman and Johnston 2014). The GFC began due to a subprime mortgage lending crisis in 2007 before expanding into a global banking crisis after the collapse of the US's 4th largest investment bank Lehman Brothers, in September 2008. Although massive bailouts were directed to limit the spread of contagion, some failed, and the global economy fell into a slump. In the UK, the trigger of the crisis began due to the withdrawal of liquidity from financial markets in August 2007, which initially hit individual banks, such as Northern Rock. Then, it became a more diffuse solvency crisis where banks experienced significant losses. The Royal Bank of Scotland Group (now called NatWest Group) and Halifax/ Bank of Scotland had been rescued by receiving extensive liquidity support from the BoE and a public recapitalisation from the UK's Government.

2.5.1.1 Stages of the crisis in the UK

Edmonds (2010) summarises the key events of the 2007/09 GFC in the UK. The following significant events highlight important conditions and factors that led to the financial collapse.

- The beginning of the liquidity crisis: The resolution by BNP Paribas to freeze three funds exposed to financial distress in the US subprime mortgage market led to exacerbated concerns over the US subprime housing market pointedly; then, the severe liquidity issues affected financial markets. As a result of the liquidity pressure, in September, the UK bank Northern Rock, which massively relied on short-term debt as the source of funding, experienced liquidity difficulties and had to ask the Bank of England for support. The leakage of this news, in turn, led to a run on the bank by its customers.

- Emergency support plan: The plan included the following measures: First, recapitalisation of banks by their governments. The UK Government contributed capital injections of £37 bn (Edmonds, 2010) into Royal Bank of Scotland Group, HBOS, and Lloyds TSB after being merged to create the single biggest banking group, the Lloyds Group Plc), in line with additional covert measures undertaken by Bank of England to support the liquidity of these individual institutions. Second, additional guarantees for bank deposits were provided by governments. In 2008, the UK's limit had increased to £50,000 from £35,000. Third, the short-selling of shares of financial institutions was banned by financial regulators. Lastly, the Bank of England directed its monetary policy support for a coordinated rate cut. The rate decreased from 5% in Sep 2008 to its lowest ever at 0.5% by March 2009. Also, a temporary cut in the VAT rate from 17.5% to 15% to help small and medium-sized businesses and homeowners was applied as fiscal policy support. By 2010, the additional guarantees for bank deposits had increased the UK's limit to £85,000.

- Partial relapse: The concerns about the stability of banks were renewed due to worse macroeconomic conditions, negative economic growth in the UK and the fall of stock markets. These concerns required governments to provide another wave of financial support. In the UK, a large-scale government insurance scheme was provided to banks for losses on their existing loans, which Lloyds Banking Group and Royal Bank of Scotland participated in.

- Slow recovery: Trust began to revert to financial markets, with asset prices increasing backed by central bank support through quantitative easing. Banks continue to rebuild their balance sheets and attempt to raise their capital, and the recovery in global stock markets supports their profitability. Furthermore, many of the supportive measures initiated by governments and central banks during the pinnacle of the financial crisis remain in place.

2.5.1.2 The 2007/09 UK bank rescue packages

The unsuccessful coordination with the EU and the continuing fall of the UK stock markets had directed the UK government to begin a comprehensive bailout plan. A £500bn bailout package was announced in October 2008 to avoid a collapse of the whole banking sector. This initial plan included three pillars: i) recapitalisation, to be done through a Bank Recapitalisation Fund, for £50bn; ii) a Credit Guarantee Scheme, through a government loan guarantee for new debt issued between UK banks, for £250bn; and iii) liquidity support, through short-term loans provided by a Special Liquidity Scheme, directed by the BoE, for up to £200bn (Mor 2018).

According to the estimations of the National Audit Office (2010), the total support in cash and guarantees provided by the UK government was around £1.2tn; Royal Bank of Scotland for £256bn, Lloyds Banking Group for £276bn, Northern Rock for £60bn, Bradford & Bingley for £46bn, Sector-wide support schemes up to £513bn, and Insolvent firms up to £11bn. The £107.6bn 2008 investment drove the UK government to acquire 84% of the Royal Bank of Scotland and 43% of Lloyds Banking Group. The government wholly acquired both Northern Rock and Bradford and Bingley. In January 2009, the UK government announced a second rescue package exceeding £50bn in response to the continuing financial crisis to raise the money banks could lend to corporations and individuals. As the support plan was voluntary, banks that benefited from the bailout package had to accept constraints on changes in corporate governance, executive pay, and dividends to existing shareholders. Also, they committed to offering flexible credit to small businesses and homeowners. Banks such as Standard Chartered, HSBC Group and Barclays announced their support for the plan but declared their reluctance to the government recapitalisation. In contrast, the Royal Bank of Scotland and Lloyds TSB and HBOS demanded government funding.

In the case of the UK financial system, the event required more than just additional funds. With the continuing banks' need for the government's help and support, the costs forced on the government continued to increase; therefore, the government enacted new legislation for regulating banks further and being capable of intervening in a preventive manner in the future. By new rules authorised through the Banking Act 2009, the FSA and the BoE acquired powers to define the viability of the UK financial institutions and to use stabilisation measures such as selling all or parts of the business to a private sector purchaser or transferring them to a "bridge bank" for organising the systematic dismantling. Furthermore, the Treasury maintains the right to take a bank into public ownership (Avgouleas 2009). The Banking Act 2009, therefore, allowed significant powers to force the resolution of a bank considered a risk for domestic financial stability. However, changes and additional instruments agreed on in the course of 2009 could not reduce the costs imposed on the government resulting from massive bank failures. As a result, the most significant outcome of the financial crisis in the UK was the restructuring of regulatory oversight. Notably, the Financial Service Authority's performance was criticised for failing to interfere early on and giving up on self-confident bank management. According to Avgouleas (2009), the failure of the FSA started when it approved Northern Rock's application for the Basle II waiver in June 2007. This statement aligns with Lastra (2008), who argues that Northern Rock was a victim of its funding structure, not the subprime crisis.

The UK bailout scheme has inspired many policymakers abroad. Quaglia (2009) argues that the plan changed the US Troubled Asset Relief Plan, and the reformation of banking regulation in 2009 was considerably comprehensive because it went further than in other European countries. After over a decade of financial service market reform and establishing the FSA, regulatory control was returned to the BOE. The Treasury proved itself to be a fundamental player in banking regulation. The UK is commonly cited as a liberal market economy with limited intervention; nevertheless, this is no longer accurate in terms of banking.

2.5.2 Basel III

This section overviews the third Basel Capital Accord, known as Basel III. The Basel Framework is the set of measures of the Basel Committee on Banking Supervision (BCBS) as a primary global standard setter for the bank's prudential regulation. Basel III refers to an internationally approved set of measures formed by the BCBS in response to the global financial crisis of 2007/09. These measures strengthen banks' regulation, supervision, and risk management. Like other Basel standards, Basel III's are the minimum requirement for internationally active banks, where members must implement and apply standards in their jurisdictions within the period specified by the Committee (King and Tarbert 2011). In 2010, the member states of the G-20 officially endorsed Basel III, which aimed to increase the quality and quantity of capital banks must hold. Alongside this development is the BCBS's comprehensive reassessment of risk coverage assumptions and guidelines. The regulatory model recommended by the Basel Committee is perceived as a prerequisite for the proper functioning of global banking systems.

In this context, the capital adequacy ratio has received special attention from international regulatory authorities as it is one of the essential regulatory tools used to control and scrutinise a bank's financial health. Regulators see Basel III as an essential measure of the safety and soundness of deposit-taking institutions. They consider capital as a safety margin capable of absorbing potential losses. In this context, Basel III breaks down Tier 1 capital into "Common Equity Tier 1" and "Additional Tier 1". The Common Equity Tier 1 must account for at least 4.5% of a bank's Risk-Weighted Assets (RWAs). The Additional Tier 1 capital must account for at least 1.5% of a bank's RWAs. In addition, Tier 2 capital is arranged at 2.0% of a bank's RWAs, giving together a minimum of 8% total capital ratio (Mili et al. 2017).

The capital ratio is calculated by dividing an institution's total (Tier 1 capital + Tier 2 capital) by its Risk-Weighted Assets (RWA). Bank of England (2014a) defines these terms as follows. Tier 1 capital for a financial institution is the sum of its Common Equity Tier 1 (CET1) capital and Additional Tier 1 (AT1) capital. The CET1 must be available to the organisation for unrestricted and rapid use to cover risks or losses as soon as these occur. It contains paid-up capital and the institution's associated share premium accounts, accumulated other comprehensive income, retained earnings, other reserves, and funds for general banking risk. AT1 capital includes paid-up capital instruments and their associated share premium account. Commonly, they are issued as hybrid debt instruments that can be converted to CET1 instruments upon trigger events. These trigger events occur when the institution's CET1 capital ratio falls below 5.125% or a level higher than 5.125% if specified in terms of the instrument. The AT1 instruments must not have any features that could hinder the institution's recapitalisation if the trigger events occur. The Tier 2 capital for an institution includes subordinated loans and capital instruments with associated premium accounts. The claims on the loan or instrument must be subordinated to all non-subordinated creditors' claims. It should not be secured or subject to a guarantee that enhances the seniority of its claim. The RWAs specify the minimum amount of regulatory capital banks must hold to maintain their solvency. This amount is based on a risk assessment for each bank's risk exposure, market, credit, operational, counterparty and credit valuation adjustment risks. The riskier the assets, the higher the RWAs and the more outstanding regulatory capital required. This research expects a negative association of capital adequacy with bank profitability.

The Basel III framework refined the capital adequacy ratio by increasing its minimum requirement from 8% to 10.5%. Following this act, the Basel III regulatory accord revised principles of liquidity risk management (2008), and two quantitative measures, the Liquidity Coverage Ratio (LCR) (2013) and the Net Stable Funding Ratio (NSFR) (2014), have been introduced to tackle the liquidity risk and improve its management (Mennawi and Ahmed, 2020). These new frameworks were sought to limit banks' investment options and risk strategies to resolve short- and long-term liquidity management issues. The measures are intended to boost banks' liquidity support and financial stability. The LCR seeks to ensure banks have enough liquidity to provide short-term, up to one month, coping with liquidity problems. The NSFR intends to guarantee that banks have adequate, stable assets to solve long-term liquidity problems for one year. NSFR addresses more fundamental changes in the asset-liability liquidity mismatch (Sidhu et al. 2022).

The impact of Basel III is likely diverse for investors, but it should direct to safer financial markets, banks, bond investors and more stability for stock market investors. A better understanding of Basel III regulations enables investors to understand the financial sector moving forward while helping them develop macroeconomic views on the international financial system's stability and the world economy. The Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), explained above, will contribute to the present research to investigate their impact on UK commercial banks' financial performance (profitability and efficiency).

2.5.3 Brexit

The UK's economic and political environment has been challenged because of leaving the European Union, considered one of Britain's most significant political events during the 21st century. Brexit refers to the UK's exit process from the European Union, shaped by the 2016 referendum. The process of Brexit started in June 2016, when voters in the United Kingdom determined to leave the European Union. It was scheduled with the definitive withdrawal of the UK from the EU on the 1st of Jan 2021. Since February 2016, when the date of the referendum was settled, the pros and cons of this scenario have been much debated between the proponents and opponents of that decision (Andreea 2017). According to Evans and Menon (2017), Brexit supporters considered the EU an economic opportunity for the UK. They tended to be sympathetic towards the free market and free trade ideas, viewing the regulatory nature of the EU as imposing on personal market freedom. This point of view aligns with Bateman (2016), who states that proponents of free trade post-Brexit hoped to strike trade deals with nations outside the EU. They see Brexit as needed for Britain to be free to trade with countries such as the US.

There is no doubt that Brexit immediately impacted the UK economy. According to Sampson et al. (2020), the referendum increased UK inflation by 1.7 percentage points in 2017, resulting in an annual cost of around £400 for the average British household. Savage and McKie (2018) estimated that the economic costs of Brexit were 2.5% of GDP. Giles (2017) found that the Brexit referendum decreased British national income by 0.6% and 1.3%. Chen, Mizen and Bloom (2018) stated that the uncertainty around Brexit decreased investment by businesses by around six percentage points and caused a reduction in employment by 1.5 percentage points. Investigating the economic impact of Brexit-induced reductions in migration, Portes and Forte (2017) found a significant adverse effect on UK GDP per capita (and GDP), with marginal positive effects on wages in the low-skill service sector. Atkinson (2022) argued that Brexit had reduced the openness and competitiveness of the British economy.

As financial institutions are sensitive to such events, the banks' financial performance (profitability and efficiency) is subjected to be affected by Brexit. For comparing purposes, the impact of Brexit on banks will be analysed by investigating the determinants of UK commercial bank’s profitability and efficiency before and after Brexit.

2.5.4 Covid-19 pandemic

The Covid-19 pandemic has caused global collapse, economic inactivity and loss of jobs that are exceptional in scale and speed. Most of the small and large businesses across every country globally have had to close their doors to customers and workers. The sharp decrease in businesses' revenues and households' incomes resulted in the first global recession, presenting the global financial system with the most significant stress event since the global financial crisis of 2007/09 (Demirgüç-Kunt, Pedraza and Ruiz-Ortega 2021). The crises vary in their effect levels based on the sector they affect and their spread (locally or internationally). Over a decade ago, the financial system, mainly banks, was the epicentre of the global financial crisis and its fundamental cause and trigger. In contrast, the Covid-19 pandemic is the epicentre of the crisis this time, while the banking sector is seen as a part of the solution rather than the problem.

Regarding the UK, the Bank of England's response to the pandemic was clear and compelling. The BoE was performed to save jobs and support the UK economy through measures and determinations. In March 2020, the BoE reduced the bank rate (Bank of England 2020a). The cut in the Bank Rate offered the UK banks and building societies long-term funding at interest rates of 0.1%. This results in cheaper loans for businesses and households. That reduced the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households. Moreover, at the end of March 2020, the Prudential Regulation Authority accepted the boards' decisions of the largest UK banks (Barclays, HSBC, Lloyds Banking Group, NatWest, Santander UK, and Standard Chartered) to suspend dividends and buybacks on ordinary shares until the end of 2020. At the PRA's request, these banks also cancelled payments of any outstanding 2019 dividends and restricted cash bonus payments to senior staff (Bank of England, 2020d).

According to the Office for National Statistics (2022a), the availability of loans to businesses and households has increased since the start of the pandemic, which contrasts with the experience of the 2007/09 global financial crisis. Also, the asset holdings of household deposits increased sharply during the pandemic, reflecting the results of "forced" savings due to public health restrictions. Businesses also raised deposit holdings, which might have been a preventive response to more uncertain business circumstances. Moreover, adults have declared an increase in using credit more than usual. This is conceivably in reaction to the rising cost of living, whereas the rise in business deposits during 2022 indicates lower business confidence and more significant uncertainty.

2.6 Summary

This chapter provided an overview of the UK financial system, focusing on the banking sector. The chapter was organised into five main sections. A brief description of the UK financial system, giving a general look at its components, was presented in 2.2. A comprehensive explanation and classification of the UK monetary financial institutions were given in Section 2.3. 2.4 presented the UK financial regulators, providing a discussion on the roles of the Bank of England (BoE), the Financial Policy Committee (FPC), the Financial Conduct Authority (FCA), the Prudential Regulation Authority (PRA), and Her Majesty's Treasury (HM Treasury). Lastly, some recent financial, political, and economic events were discussed in Section 2.5. These events included the 2007/09 global financial crisis, summarising its stages in the UK, and the rescue packages and the schemes that were taken to overcome its adverse impacts on some UK banks in response to the crisis. Also, the section discussed the introduction of the Basel Capital Accord (Basel III) by highlighting the required capital banks must hold as a response to the 2007/09 global financial crisis. The section overviewed the UK's withdrawal from the EU (Brexit). Lastly, the section sheds light on the most recent global event (Covid-19) pandemic by briefly discussing its effect on the UK economy and the Bank of England's actions to absorb its economic effects.

Chapter 3: Literature Review on Bank Profitability

3.1 Introduction

This chapter is dedicated to reviewing the related literature on the determinants of bank profitability. The chapter is organised as follows. Section 3.2 introduces the concept of profitability to give the reader a better understanding of the concept of "profitability" before moving to the rest of the chapter. Section 3.3 comprehensively explains profitability from a firm's perspective and how it is considered a financial performance indicator. Section 3.4 explains the profitability measures by presenting the most used financial ratios. Section 3.5 discusses the literature on bank profitability by addressing the studies conducted on this topic. It detailed the regions, data samples, variables, and the results of these investigations. Lastly, a summary of the chapter is given in Section 3.6.

3.2 The concept of profitability

Profitability is ancient and valuable if haggling exists between two parties. Even now, the ancient merchants, bankers and lenders aimed to gain some profit from their actions. Nevertheless, the financial ratio analysis appeared in the nineteenth century, and profitability measurement was part of it. Borrowers and administrators were primarily interested in profitability, while lenders and bankers were interested in the firm's ability to pay its obligations. Horrigan (1968) notes that, in 1919, the Du Pont Company (an American chemical company) started to use a ratio "triangle" system to evaluate its operational outcomes. The top of the triangle was the Return-on-Investment ratio (ROI).

In the literature, there is a variation of different meanings for the firm's profitability. Van Horne and Wachowicz (2008) state that profitability is the firm's ability to produce income by sacrificing expenses, considering the time lag between expenses and incomes in the definition of profitability. It can also be defined as the discount rate in which the benefit (returns) is as great as the sacrifice (expenses). From this perspective, the definition of profitability coincides with the internal rate of return (IRR). Another path to address profitability is the owner's point of view. In this case, profitability can be defined as a ratio of income to capital. From this aspect, the definition of profitability matches the concept of return on investment (ROI) (Brealey, Myers and Allen 2011). The fundamental idea in all definitions of profitability is the firm's ability to produce a profit, calculated as income minus expenses.

3.3 Firm's profitability

Profitability is a fundamental concept in finance, accounting, and economic discussion. Due to its commonness, it is a multifaceted term used on different economic levels. In addition to liquidity and solvency, Chakravanty (1986) considers profitability as the firm's financial performance's head indicator. Therefore, profitability is essential for the sustenance of a firm's functioning. Profitability is vital for all profit-seeking institutions, as reaching profit is the economic purpose of every business. The goals can differ from firm to firm, considering the nature of its activities. These goals include supplying services, employment, continuity, and environment. However, it is relevant to mention that some organisations, such as non-profit organisations, have different economic aims than firms. Deasy (2003) argues that profitability indicates a firm's market power, so it assesses whether it has made profits over the average return on the products. It can also give a critical insight into the degree of the market's competitiveness, as opposed to individual firms' market power. This applies to oligopolistic markets where no single firm is dominant but is concerned about the degree of competitive pressure the few firms impose on each other. Profitability is measured and investigated at national, industry, firm, investment, and product levels. Estimating profitability from many different perspectives on all these levels is reasonable. In this research, the subject of interest is profitability at a bank level.

3.4 Measurement of profitability

Profitability measurement is an integral part of measuring organisational performance, just as the value of productivity measurement. However, the point of view is slightly different, and the purposes are not the same. In profitability measurement, the aims are primarily economic by focusing on the "quality" of results, while the measurement's productivity purposes by focusing on the "quantity" of results (Holloway, Lewis and Mallory 1995). Considering profitability as a measure of overall firms' performance and capturing all of the organisation's activities, good and bad, the National Research Council (1979, p.167) defines profitability as "The best overall indicator of company performance: It measures the outcome of all management decisions about sales and purchase prices, levels of investment and production, and innovation as well as reflecting the underlying efficiency with which inputs are converted into outputs". It can be understood from this definition that profitability measurement should present most of the information that an institution needs. Nevertheless, this is only partially true. Profitability measurement can be seen as a measure of reaching the firm's aim or outcome. However, to be profitable, there is a need to measure other drivers (factors) that all contribute to the firm's outcomes. Based on these measurements' results, decisions can be made which help the firm achieve the planned aims. The firm's profitability can be measured in several ways, and the available data and the needed financial information decide how to measure it. The most often profitability measures used are financial ratios based on financial statements analysis. Also, many different ratios are based on a firm's money flows. The profitability measures are divided into two basic types: relative and absolute measures. The relative measure links the profit or margin, as a proportion, to some dimensions that describe the determinants (such as sales/revenues, equity, and total assets) of this profit or margin. In comparison, the absolute measure describes the profit or margin itself.

The literature shows several measures of the overall firm's profitability. Aerts and Walton (2017) present the financial ratios that draw the ways of expressing relative profitability. The primary and widely used ratios in the bank profitability literature are Return on Assets (ROA), Return on Equity (ROE), and Net Interest Margin (NIM). These profitability ratios are selected for empirical analysis for this research's purposes. A comprehensive explanation of the ratios will be presented in Chapter 3 Chapter 3:of the thesis. Other profitability ratios include net profit margin, gross operating margin, net operating margin, earnings per share, and return on capital employed[8]. However, it is not reasonable to explain these ratios here as they are not relevant to the purpose of this research. In summary, profitability is also a comprehensive concept as it reflects the monetary process of a firm, and it is usually measured in money values and describes a firm's ability to produce a profit.

Tobin's Q ratio can measure the market performance of banks. The ratio, introduced by Nobel laureate James Tobin in 1969, appears as a crucial measure to assess the market's perception of a firm's value and capital investment strategies (Cao, Lorenzoni and Walentin, 2019). It is calculated by dividing a firm's market value by its assets' replacement cost. A value greater than 1 implies that the market values that firm's assets above their replacement cost, suggesting favourable investment conditions. However, this ratio is eliminated from this research (for both profitability and efficiency investigations) due to the unavailability of market value data for most private commercial banks included in this research; it is impossible to use this ratio to measure banks' market performance.

3.5 Review of literature on bank profitability

The term bank profitability is usually expressed as a function of two types of determinants: internal and external. The internal determinants could be titled micro or bank-specific factors of profitability subjected to the management's control. Researchers commonly connect bank profitability to quality management, assessed in terms of senior officers' awareness and control of their policies and performance. In an

[8] More about these profitability measures of a firm and how to calculate them with practical examples can be found in the publication (Aerts and Walton 2017, pp. 251-272).

investigation into the determinants of European bank profitability, Staikouras and Wood (2011) argue that management decisions regarding loan portfolio concentration were essential factors in banks' performance.

The external determinants of profitability refer to variables that are not correlated to bank management but show the industrial and legal conditions that control or affect the financial institutions' operations and performance. To date, the literature on investigating bank profitability (Short 1979; Smirlock 1985; Berger 1995a; Staikouras and Wood 2011; Alper and Anbar 2011; Tan and Floros 2012; Petria, Caprarub and Ihnatov 2015) have underlined several variables for both types of determinants, concerning the nature and aim of each study. The empirical analysis assumes that profitability reflects management efforts to maximise shareholder wealth and not engage in expense preference behaviour.

Following early work by Short (1979) and Bourke (1989), many studies have tried to name bank profitability determinants. These studies have focused their examinations either on cross-country evidence (Molyneux and Thornton 1992; Demirguc-Kunt and Huizinga 1999; Goddard, Molyneux and Wilson 2004; Micco, Panizza and Yañez 2007; Pasiouras and Kosmidou 2007), or on the banking system of individual countries (Berger, Hanweck and Humphrey 1987; Berger 1995; Athanasoglou, Brissimis and Delis 2008; García-Herrero, Gavilá and Santabárbara 2009). In most of the mentioned studies, variables such as size, risk management, deposits, loan ratio, loan loss provisions, regulatory capital, and expense management were applied as bank-specific determinants of banking profitability. Effective tax rates, inflation, and economic growth were industry-specific factors influencing banks' profitability.

Bank size is expressed by the logarithm of the bank's total assets. It rates the importance of deposits and loans and the larger banks' ability to access the asset markets. This could imply higher profitability, which proves that a bank's size positively and significantly affects interest margins. Bouzgarrou, Jouida and Louhichi (2018) report a significant positive impact of bank size on interest margins as larger banks could benefit from higher product and loan diversification possibilities or economies of scale. It is the most used accounting variable in banking investigations, and most of the literature recommends a positive correlation between profitability and bank size. Smirlock (1985) found a positive and meaningful relationship between market share (total assets of a bank to total assets of the banking sector) and bank profitability.

Furthermore, Short (1979) argues that size is closely correlated to the bank's capital adequacy as relatively large-sized banks tend to boost less expensive capital and hence seem more profitable. Similarly, Bikker and Hu (2002) and Goddard, Molyneux and Wilson (2004) relate bank size, particularly small to medium-sized banks, to capital, hence profitability. Aysun (2016) argue that large-sized banks play a crucial role in regional business cycles. This argument aligns with studies by Demsetz, Saidenberg and Strahan (1996) and Feng and Serletis (2010), who suggest that having large-sized banks brings more stability to the economy. This stability occurs due to their willingness to take fewer risks to shield their franchise value, lower service costs, and higher informational rents, which prevent informational dispersion. As a result, banks can more efficiently diversify risk and generate more profits.

Olson and Zoubi (2011) studied the efficiency and profitability of banks in ten Middle East and North Africa (MENA) countries. They found a positive association between bank size and profitability, which implies that larger MENA banks are more cost and profit-efficient. Berger, Hanweck and Humphrey (1987) recommend that little cost saving could be obtained by raising the bank size. Athanasoglou, Brissimis and Delis (2008) argue that the relationship between size and profitability is not assumed to be linear. The literature shows that collective efforts have been made to address the relationship between bank size and profitability. Nevertheless, various conclusions indicate an opportunity to develop our comprehension of the concept.

Berger and Bouwman (2007) conclude that the correlation between capital and liquidity creation is positive and significant for large-sized banks, insignificant for medium-sized banks, and negative and significant for small-sized banks. Tran, Lin and Nguyen (2016) found that regulatory capital and liquidity creation affect each other positively after controlling for bank profitability. Moreover, regulatory capital is negatively related to bank profitability for higher-capitalised banks and positively related to profitability for lower-capitalised banks. Other authors, such as Kosmidou, Tanna and Pasiouras (2008), found that capital strength is the primary determinant of UK banks' profits. Furthermore, the cost-to-income ratio and bank size negatively impact bank profits.

Further, liquidity is negatively related to Net Interest Margin (NIM) but positively related to Return on Assets (ROA). The impact of loan loss reserves is also unclear, being positive and significant on NIM but negative and insignificant on ROA. They also found that external factors such as GDP growth and inflation positively affect bank performance.

Holden and El-Bannany (2004) investigate whether the investment in information technology systems, measured by the number of cash machines, affected bank profitability in the UK from 1976 to 1996. Their results show no support for the influences of the existence of the ATM network or its membership. This may be a peculiarity of their study's data period since the network only became important in the 1990s. However, with the improvement in the technology sector and the increase in access to the internet nowadays, applying this variable to new research could show different results, as the service provided by cash machines these days exceeds being just a tool for withdrawing cash. Alper and Anbar (2011) investigated the profitability of 10 Turkish commercial banks, proxied by return on assets and return on equity. The results show that asset size, real interest rate, and non-interest income positively and significantly affect bank profitability. The size of the credit portfolio and loans under follow-up negatively and significantly impact bank profitability.

Homaidi et al. (2020) examine the impact of internal and external determinants of Indian commercial banks' profitability from 2008 to 2017. The results show that bank size, asset quality, liquidity, asset management, and net interest margin are important internal determinants that affect ROA. Capital adequacy, deposits, operation efficiency, gross domestic product and inflation rate significantly negatively impact ROA. The results also indicate that capital adequacy, bank size, operation efficiency, gross domestic product, and inflation rate negatively influence ROE. However, asset quality and management positively affect ROE, but liquidity, deposits, net interest margin, and non-interest income significantly affect ROE. Kumar and Bird (2020) investigate the factors influencing banks' profitability in India and China. They found that credit quality, bank size, and cost management are significant factors in banks' profitability in India and China. The loan-to-deposit ratio of the banks is also essential. It has a positive impact on banks' profitability in China but a negative impact on banks' profitability in India. Using a sample of 122 Japanese banks from 2004 to 2018, Kumar, Thrikawala and Acharya (2021) investigate whether financial inclusion improves bank profitability. Their outcomes show that branch contraction reduces Japanese banks' profitability, although the numbers of loan accounts and cash machines do not affect bank profitability. In contrast, bank-specific variables such as cost management, credit risk management, and bank size are the fundamental drivers of profitability.

Feng and Wang (2018) directed a study to assess the reasons for the low profitability of European banks compared to their U.S. counterparts from 2004-2014. They found that the EU banks' profitability was lower and declined further in the post-crisis period. The lower profitability was attributed to EU banks' lower returns on earnings assets, higher funding costs, and lower scale efficiency. Also, the significant increase in funding costs was partly due to the less aggressive rate cuts by the European Central Bank. In addition, the deterioration of EU banks' relative profitability in the post-crisis period was caused by increased relative funding costs and decreased relative returns on earnings assets, technical efficiency, and scale efficiency.

Research in the United Kingdom has been limited. To the author's knowledge, two recent studies have been directed in the UK banking sector context. O'Connell (2022) investigated bank profitability determinants in the UK using unbalanced panel data for 16 UK-owned banks operating within the UK banking sector from 1998–2018, consisting of 241 observations. The findings of this study show that longer-term interest rates and inflation rates significantly affect bank profitability. Also, profitability persists moderately within the UK banking sector, indicating a departure from a perfectly competitive market structure. Grose et al. (2021) analysed bank profitability in a sample of UK commercial banks from 2007–2018. They used Return on Average Assets (ROAA), Return on Average Equity (ROAE) and Net Interest Margin (NIM) as proxies of profitability, while explanatory variables included a set of internal and external factors. Their results indicate that bank size has a negative role in profitability due to the existence of economies of scale for the smaller banks and diseconomies for the larger ones. Also, no relationship was found between either GDP or liquidity and overall UK bank profitability.

Regarding recent studies in UK banks, the present research differs from those mentioned above in three aspects. First, the present research provides comprehensive and more reliable results that can be generalised for the UK banking sector by using data from 50 UK banks chosen at a group level, representing 80.19% of the UK banking sector's total assets over the period 2010-2021 of a sample includes diverse types and sizes of banks representing public and privet banks, domestic and foreign banks, commercial banks, investment banks, bank holding companies, finance companies, Islamic banks, and savings banks. Second, As the econometric analysis in most empirical literature does not consider classical problems such as endogeneity and unobservable heterogeneity of the data, which are common in studies analysing managerial decisions (Arellano and Bover 1990), the present research overcomes this issue by using a large sample consisting of 549 observations that will be analysed by using a dynamic panel GMM model that allows to include the proxies of banks profitability as a lagged variable among the regressors for the regression analysis. This procedure helps to solve the endogeneity problem, as banks' profit persists over time (Berger et al. 2000; Goddard, Molyneux and Wilson 2004). Lastly, the current research used data from a unique period (2010-2021) that covered the most recent financial and economic events, including the post-2007/09 global financial crisis, the Basel III, Brexit, and the most recent crisis (Covid-19 pandemic). With the abovementioned contributions, the present research's findings will provide an updated outlook on UK bank profitability. Table 3.1 provides an overview of investigations on bank profitability with their essential findings.

Table 3.1: A summary of previous investigations on bank profitability.

Author(s)	Methods	Variables used	Sample size and origin	Summary of findings
Short (1979).	OLS	DVs: Banks' profit rates. IVs: Concentration ratio, Capital scarcity, Leverage ratio, Government ownership, Rate of growth of assets, and Bank size.	Sixty banks in Canada, Western Europe, and Japan.	A greater concentration leads to higher profit rates—a statistically significant inverse relationship between return on capital and government ownership.
Smirlock (1985).	OLS	DVs: Return on equity, return on total capital, and return on total asset. IVs: Concentration, total market deposit, growth in market deposits, demand deposits to total deposits ratio, and bank size.	2,700-unit state banks in the seven-state area under the authority of the Federal Reserve Bank of Kansas City.	Concentration adds nothing to explaining bank profit rates once the market share is accounted for properly. Market share is positively and significantly related to profitability.
Bourke (1989).	OLS and FE	DVs: Return on capital, return on assets. IVs: Staff expenses, capital ratios, liquidity ratio, concentration ratio, government ownership, interest rates, market growth, and inflation.	90 banks from twelve countries or territories in Europe, North America, and Australia.	Capital ratios, liquidity ratios, concentration and interest rates positively affect profitability. Staff expenses have an inverse correlation with return on assets and an inverse relationship between return on capital and government ownership.
Molyneux and Thornton (1992).	OLS	DVs: Return on assets, return on capital. IVs: Government ownership, concentration ratio, long-term bond rate, growth in money supply, capital, and reserves as a per cent of total assets, and staff expenses.	1,108 European banks across eighteen European countries.	A positive relationship between return on capital and concentration. Staff expenses and concentration have a positive correlation with return on assets. State-owned banks generate higher returns on capital than their private-sector competitors. Government ownership, capital ratios and nominal interest rates positively relate to profitability, while liquidity ratios have a weak inverse relationship with profitability.
Berger (1995b).	FE	DVs: Return on equity and Capital to asset ratio. IVs: Bank's share of market deposits, Growth of deposits, operating costs to total assets, risk-weighted assets to total assets, non-performing loans to total assets.	US commercial bank.	A strong positive relationship between capital and earnings.
Sufian (2009).	OLS	DVs: Return on assets. IVs: Liquidity, size, credit risk, operating costs, branch networks, Leverage, GDP, and inflation.	Chinese state-owned and Joint-stock commercial banks.	Size, credit risk, capitalisation, GDP and inflation positively relate to profitability, while liquidity, overhead costs, and network embeddedness have negative impacts. State-owned banks with higher levels of liquidity tend to be more profitable.
Staikouras and Wood (2011).	OLS and FE	DVs: Return on assets and return on equity. IVs: Loan to assets ratio, equity to assets ratio, provisions for loan losses to total loans ratio, H-H index, level of interest rates, concentration ratio, bank size, inefficiency, and Growth rate of the GDP.	685 banks in 13 European countries.	ROA has a positive correlation with the Gap and EA variables and a negative correlation with the LLP/TL variable. A negative correlation of assets with EA and OA and a positive with MSH. Positive correlation of gap with EA, of EA with OA, and a negative one of LA with EA, and of IR with DEV and dGPI.

Dietrich and Wanzenried (2011).	GMM	DV: Return on average assets, Return on average equity, and Net interest margin. IVs: Capital adequacy, operational efficiency, credit quality, growth of deposits, bank size, interest income share, funding costs, bank age, bank ownership, nationality, effective tax rate, GDP growth, term structure of interest rates, and H-H index.	372 commercial banks in Switzerland.	Larger and smaller commercial banks were more profitable than medium-sized banks before the crisis. State-owned banks were more profitable than privately owned banks during the financial crisis. Funding costs significantly negatively impacted the return on assets before the crisis, while the H-H index had a positive one. The positive impact of bank age and the negative one of growth of deposits and taxation on banking profitability.
Tan and Floros (2012).	GMM	DVs: Return on assets and Net interest margin. IVs: Bank size, credit risk, liquidity, taxation, capitalisation, cost efficiency, labour productivity, concentration, banking sector development, and inflation.	101 Chinese banks.	Cost efficiency, banking sector development, stock market development and inflation are determinants of bank profitability in China. Credit risk is negatively related to ROA but positively related to NIM. Liquidity and bank size are significantly related to NIM but not ROA and labour productivity positively affects ROA only.
Petria, Caprarub and Ihnatov (2015).	OLS	DVs: Return on average assets and return on average equity. IVs: Bank size, capital adequacy, credit risk, management efficiency, liquidity risk, market concentration, inflation, and economic growth.	1,098 banks from EU27 countries.	Cost to income ratio and Credit risk have a negative impact on both dependent variables. Operating income, solvency, competition, and GDP growth have a positive significant impact on both return on average assets and return on average equity.
Tan (2016).	GMM one-step system.	DVs: Return on assets, net interest margin, return on equity, and profit margin. IVs: Bank size, liquidity, risk, capitalisation, cost management, diversification, labour productivity, taxation, competition, banking sector development, stock market development, inflation, and GDP growth rate.	41 Chinese commercial banks.	Taxation has a significant and negative impact on ROA, NIM and PBT. Banks with higher labour productivity and higher overhead costs have higher profitability. Joint-stock commercial banks and city commercial banks have lower ROA, NIM and PBT than state-owned commercial banks.
Djalilov and Piesse (2016).	GMM technique; one-way error	DVs: Return on equity. IVs: Capital, credit risk, cost, size, H-H index, GDP growth, and inflation.	Banks in 25 Central and Eastern Europe.	The coefficients on capital are positive and significant, implying that better-capitalised banks are more profitable in early transition countries. The coefficients on credit risk are significant but with different signs—a negative effect of credit risk on bank profitability in the late transition countries.
Elisa and Guido (2016).	GMM	DVs: Return on equity. IVs: Deposit ratio, asset quality ratio, bank size, capital ratio, and loan ratio.	28 European banks.	Capital ratio and size positively impact bank profitability, while higher asset quality results in lower profitability. Banks with higher deposit ratios tend to be more profitable. Size and capital strength are significant determinants of European banks' profits. Asset quality ratio is an internal determinant of bank profitability in Europe, but its impact is negative. The effect of the deposit ratio on ROE is positive and significant.

Yao, Haris and Tariq (2018).	GMM	DVs: Return on assets, Return on equity, Net interest margin, and Profit margin. IVs: Bank size, solvency, credit quality, liquidity, operational efficiency, financial structure, funding cost, operating cost, labour productivity, bank type, industry concentration, banking sector development, inflation, and GDPR rate.	28 banks in Pakistan.	Credit quality, operational efficiency, banking sector development, inflation, and industry concentration are negatively and significantly related to profitability. Banking sector development and industry concentration are significantly negatively related to all profitability indicators. A significant positive impact of GDPR on all profitability indicators.
Homaidi et al. (2020).	Pooled, fixed, and random effects and GMM	DVs: Return on assets and return on equity. IVs: Bank size, capital adequacy, asset quality, liquidity, deposits, assets management, operating efficiency, net interest margin, non-interest income, GDP growth and inflation rate.	Thirty-seven commercial banks are listed on the Bombay Stock Exchange (BSE), India.	Bank size, asset quality, liquidity, asset management, and net interest margin are important internal determinants of return on assets. Capital adequacy, deposits, operation efficiency, gross domestic product and inflation rate negatively impact return on assets. Capital adequacy, bank size, operation efficiency, gross domestic product and inflation rate significantly negatively influence return on equity, while Asset quality and asset management have a positive one.
Le and Ngo (2020).	GMM	DVs: Return on assets and net interest margin. IVs: Number of cards, number of ATMs, number of points of sale, bank efficiency, capital adequacy, credit risk, financial market development, market power, GDP growth, inflation, and financial contagion (2007/09 crisis).	23 countries	The number of issued bank cards, ATMs, and points of sale terminals can improve bank profitability. A negative relationship between bank overhead costs and profitability. The negative impact of market power on bank profitability suggests that a less concentrated banking system improves bank profitability. More significant financial development has a positive impact on bank profitability.
Grose et al. (2021)	GMM	DVs: Return on average assets, return on average equity, and net interest margin. IV: Credit risk, liquidity, bank size, concentration, inflation, loan and GDP.	Sample of UK commercial banks	Bank size has a negative role in profitability due to the existence of economies of scale for the smaller banks and diseconomies for the larger ones. Also, no relationship was found between either GDP or liquidity and overall UK bank profitability.
Kumar, Thrikawala and Acharya (2021)	OLS and GMM	DVs: Return on assets, return on average equity. IVs: Number of loan accounts, number of ATMs, number of bank branches, cost-to-income ratio, capital adequacy ratio, nonperforming loan ratio, bank size, inflation rate, Interest rate, GDP.	122 Japanese banks	Branch contraction reduces the profitability of Japanese banks. The number of loan accounts and automated teller machines (ATMs) do not affect bank profitability. Bank-specific variables: cost management, credit risk management, and bank size are critical drivers of profitability.
O'Connell (2022)	GMM	DVs: Return on average assets, return on equity, and net interest margin. IVs: Capital, credit risk, deposits, liquidity, productivity, size, concentration, inflation, loan growth.	16 UK-owned banks	Longer-term interest rates and inflation rates significantly affect bank profitability. Also, profitability persists moderately within the UK banking sector, indicating a departure from a perfectly competitive market structure.

Note: OLS: The Ordinary Least Square model.; FE: The Fixed Effect model; GMM: The Generalised Method of Moment model. DVs: Dependent variables. IVs: Independent variables.

The literature review supports that several various determinants could affect profitability. Still, it is hard to tell whether all are essential determinants in banking performance and, if they are, what their relative importance is. With this limitation, this research explores these relationships in the UK banking sector. The literature's empirical findings are various, which is assumed, given the variations in the studies' datasets, periods, investigated environments, and countries. Some prevalent variables will be used in line with other added variables to find other determinants of bank profitability in the UK banking sector.

The following chapter, Chapter 4, explains and clarifies, with a link to the related literature, the dependents and independent variables that will be used for this research to investigate UK bank profitability. The external variables consist of the industry-specific and macroeconomic factors that reflect the characteristics of the UK banking sector and the UK economy. Market concentration, industry size, ownership structure, and ownership status will be used as industry-specific variables. At the same time, the macroeconomic variables are the base rate, unemployment rate, inflation rate, GDP growth rate, Brexit, and Covid-19. The Return on Assets (ROA), Return on Average Assets (ROAA), Return on Equity (ROE), Return on Average Equity (ROAE), and Net Interest Margin (NIM) will be used as proxies for bank profitability.

3.6 Summary

This chapter presented the recent studies on bank profitability and its determinants. The chapter introduces the concept of profitability to give the reader a better understanding of the concept of profitability before moving to the rest of the chapter. Then, the chapter comprehensively explained profitability from a firm's perspective and how it is considered a financial performance indicator. Furthermore, the section on profitability measurement explained how profitability is measured by presenting the most used financial ratios. Lastly, the chapter discussed the literature on bank profitability by addressing the studies on this topic. It detailed the regions, data samples, variables, and the results of these studies. In line with some variables used in the earlier investigations, this research contributes to the literature by applying more variables that, to the researcher's knowledge, have never been used before in investigating UK commercial banks. The variables reflect the characteristics of the UK banking sector and economy.

Chapter 4: Methodology and Research Method on Bank Profitability

4.1 Introduction

The main objective of this chapter is to describe and explain the methodology and research methods for investigating the determinants of the UK banks' profitability over the period 2010-2021. This chapter explains how this research will be undertaken and how the data collected will be analysed. It is proper to distinguish between two terms, "methodology" and "method", as this chapter of the research is labelled (methodology and method) of banks' profitability. Saunders, Lewis and Thornhill (2019) give the two terms precise meanings. The term methodology can refer to the theory of how research should be undertaken. At the same time, method refers to techniques or procedures used to obtain and analyse data, including questionnaires, observation, and interviews, and quantitative (statistical) and qualitative (non-statistical) analysis techniques.

The remainder of the chapter is organised as follows: Section 4.2 presents the research questions. Section 4.3 presents the research philosophy and approach, and section 4.4 presents the data type and collection method. Section 4.5 presents the research period, sample, and data. Section 4.6 provides a detailed explanation of the determinants of bank profitability and variable selection. This section has two subsections 4.6.1 for the profitability measures and 4.6.2 for the determinants of bank profitability. Section 4.7 presents the econometric specification of the models, the profitability model, the standard estimators (Ordinary Least Squares (OLS) and Fixed Effects (FE)), and the Generalised Method of Moments GMM model that will be used for analysing the data. Section 4.8 presents the data analysis method, and lastly, a summary of the whole chapter is presented in section 4.9.

4.2 Research questions

As discussed in Chapter 3, previous studies have been directed to investigate the factors affecting the bank's profitability. Whether the studies were at a group-country or specific country level, the aims were to specify these factors as determinants of bank profitability.

This research investigates the determinants of bank profitability in the context of the UK. To the researcher's knowledge, few recent studies examined the determinants of UK commercial banks' profitability, at least in the recent decade. O'Connell (2022) investigated bank profitability determinants of 16 UK-owned banks from 1998–2018, and Grose et al. (2021) analysed bank profitability only in a sample of UK commercial banks from 2007–2018. These two studies need a more comprehensive analysis of the UK commercial banks by expanding the research sample to cover more banks. Also, other variables related to the UK banking sector's characteristics and recent events, such as Brexit and Covid-19, are used to contribute to the existing literature. To reach these aims and objectives, the current research attempts to answer the following questions:

i. What are the bank-specific, industry-specific and macroeconomic determinants of UK commercial banks' profitability from 2010 to 2021?
ii. What are the bank-specific, industry-specific and macroeconomic determinants of UK commercial banks' profitability before and after Brexit?

4.3 Research philosophy and approach

Quantitative research is commonly associated with a deductive approach when data is gathered and analysed to test a theory. Nevertheless, it could incorporate an inductive approach when data are used to develop a theory. According to Saunders, Lewis and Thornhill (2019), quantitative research methods are typically associated with positivism, mainly when the data collection techniques are predetermined and highly structured. However, Walsh et al. (2015) state that it is increasingly seen as a philosophical caricature to suggest an exclusive association between positivism, deduction, and a quantitative research design.

Based on the research onion model that had been presented by Saunders, Lewis and Thornhill (2019) to define the stages through which a researcher must pass when conducting quantitative or qualitative research, this research, based on its characteristics, aims and objectives, adopts positivism as a philosophical position to investigate the relationship between the UK banks' profitability and the internal (bank-specific) and external (industry-specific and macroeconomic) determinants. From a philosophical and methodological approach, a deductive approach is used to answer the research questions. A quantitative method is applied as this research uses secondary data, recognised as the most proper for testing the research hypotheses. The GMM models will be used as the main estimators to analyse the relationship between the performance measures (profitability and Efficiency) and the presumed independent variables. The dynamic Generalised Method of Moments (GMM) model widely exists among researchers who directed their studies using panel data. The model was presented in 1991 by Manuel Arellano and Stephen to address specific endogeneity problems. According to Baltagi (2021), the Arellano–Bond estimator is a generalized method of moments estimator used to gauge dynamic panel data models.

4.4 Data type and collection method

After defining the quantitative or qualitative research type, it is essential to define the data type to be analysed to answer the research questions. Data is divided into two main types: primary and secondary data. The collecting methods of primary and secondary data vary. The primary data are original as they are collected for the first time, while the secondary data are those that have already been published or collected by others and have already been offered through the statistical process. It could be said that primary data are to be collected initially, while in the case of secondary data, the nature of data collection work is simply that of compilation. Public opinion is essential in most studies, especially those that collect their data through questionnaires and interviews, but it is not appropriate in this research due to its aims. Therefore, this research does not consider primary data using a survey or questionnaire. Also, collecting primary data about banks, industries, and related macroeconomic variables of all the UK banks for eleven consecutive years is impossible.

It is vital to identify which type of data is needed to answer the research questions of this research and how the data will be collected. The data used to represent this research's variables are different; some data were collected and used directly as values of the variables, so they are secondary data as they are publicly published. The other values of variables were gathered from secondary data sources for generating primary data to be used as values of variables. In other words, secondary data sources (financial reports) have been used to generate primary data for this research.

The data in this research were collected from the published annual financial reports of the UK banks included in the research sample for 2010-2021. As the professional external audited firms inspected these published financial reports, they are dependable and valid. ORBIS Bank Focus and Banks' Websites were the primary sources for collecting the sample research's UK banks' annual reports. This research uses the banks' annual financial statements, balance sheets and statements of profit or loss since these statements are the heart of the financial reporting system. They were used to collect the data related to the bank-specific factors (internal variables), while the Bank of England website was accessed for collecting data related to the macroeconomics variables (external variable). Data was organised as a panel data set.

- Balance sheet

The balance sheet is a financial statement that shows the company's financial position at a given date. It has two parts: assets and liabilities. The debit side presents the economic resources, which are the corporation's assets as current, fixed, and intangible assets. In contrast, the credit side presents all claims against the company (liabilities and equity), and these, by definition, are equal to the company's assets.

Assets can be defined as the economic values of what the company holds. It has three types: i) physical assets (fixed assets) include buildings, lands, cars, machines, and equipment. ii) Financial assets (current assets) include cash, account receivables, short-term investments, and inventories. iii) Intangible assets include trademarks, patents, and goodwill. Liabilities are the first part of the credit side and can be defined as the amount of money the company is obliged to pay others. It has two types: i) current liabilities, such as payable and short-term debt, and ii) long-term liabilities, such as long-term debt. Equity is the second part of the credit side. It is defined as the amount of money that constructs a firm's capital. It is represented as percentages of ownership that allow owners to earn profits as sharing percentages (Aerts and Walton 2017).

- Statements of profit or loss

It is also known as the income statement and is the first, in order, financial statement to be presented in the annual financial report of a company. It measures the company's business operations for the accounting period (total revenues minus total expenses). A positive result means a company makes a profit, while a negative result means losing. The income statement starts with total revenue and ends with net profit/ loss after subtracting all costs, expenses, depreciation, and tax from the total revenue (Aerts and Walton 2017).

- Bank websites

The websites of banks in the research sample were accessed for collecting the missing data as some annual financial data and reports of sample banks are not presented on the Orbis Bank Focus database. Also, the downloaded annual reports were used for checking the accuracy of values, as some were slightly different from what was presented in the Orbis Bank focus database.

- Bank of England website

The website of BoE was accessed to collect data related to the macroeconomic variables used for this research, which reflect the UK economy. These variables include inflation, GDP growth, base rate, unemployment rate, and employment rate. More details about these variables are presented in Section 4.6.2.

4.5 Research period, sample, and data

The sample in this research includes 38 commercial banks from the UK banking sector. These banks were chosen at a group level from 2010 to 2021, and the year of banks' incorporation in the UK banking sector of the research sample and the availability of their annual data led to unbalanced panel data. Those data are for N = 38 banks, where 26 banks are observed in T = 12 time periods, three banks are observed in T = 11 time periods, four banks are observed in T = 9 time periods, two banks are observed in T = 8 time periods, and three banks are observed in T = 7 time periods from 2010 to 2021, giving a total of 417 observations. The banks used in the research, including their total assets, market shares compared to the whole UK banking sector and their specialisations, and the number of observations for each bank, are presented in Table 4.1.

Table 4.1: The banks and their total assets, market shares, number of observations of each bank, and their specialisations.

No	Bank	Specialisation	Total Assets (£m)/ 2021	Market Share	No. Obs.
1	HSBC Holdings Plc	Commercial Bank	2,201,831	22.87%	12
2	Barclays Plc	Commercial Bank	1,384,285	15.89%	12
3	Lloyds Banking Group Plc	Commercial Bank	886,525	9.97%	12
4	NatWest Group Plc	Commercial Bank	781,992	8.92%	12
5	Standard Chartered Plc	Commercial Bank	616,211	6.09%	12
6	Santander UK Plc	Commercial Bank	288,398	2.85%	12
7	Virgin Money UK Plc	Commercial Bank	89,100	0.88%	7
8	SMBC Bank International Plc	Commercial Bank	38,919	0.38%	12
9	The Co-Operative Bank	Commercial Bank	29,323	0.29%	12
10	Bank of Ireland (UK) Plc	Commercial Bank	22,705	0.22%	11
11	Metro Bank Plc	Commercial Bank	22,587	0.22%	12
12	Scotiabank Europe Plc	Commercial Bank	22,561	0.22%	11
13	ICBC Standard Bank Plc	Commercial Bank	19,554	0.19%	12
14	Aldermore Bank Plc	Commercial Bank	15,583	0.15%	12
15	Paragon Bank Plc	Commercial Bank	13,506	0.13%	8
16	AIB Group (UK) Plc	Commercial Bank	12,688	0.13%	12
17	Close Brothers Group Plc	Commercial Bank	12,035	0.12%	12
18	Shawbrook Bank Limited	Commercial Bank	11,023	0.11%	11
19	Bank of New York Mellon Ltd (The)	Commercial Bank	10,612	0.10%	12
20	Sainsbury's Bank Plc	Commercial Bank	7,458	0.07%	12
21	C Hoare & Co	Commercial Bank	6,004	0.06%	12
22	British Arab Commercial Bank Plc	Commercial Bank	3,715	0.04%	12
23	Oaknorth Bank Plc	Commercial Bank	3,245	0.03%	7
24	Secure Trust Bank	Commercial Bank	2,886	0.03%	12
25	ABC International Bank Plc	Commercial Bank	2,711	0.03%	12
26	FBN Bank (UK) Limited	Commercial Bank	2,412	0.02%	12
27	Julian Hodge Bank Limited	Commercial Bank	2,302	0.02%	12
28	United Trust Bank Limited	Commercial Bank	2,254	0.02%	9
29	Europe Arab Bank Plc	Commercial Bank	2,190	0.02%	12
30	ICICI Bank UK Plc	Commercial Bank	2,148	0.02%	12
31	ICBC (London) Plc	Commercial Bank	1,991	0.02%	12
32	Bank of China (UK) Ltd	Commercial Bank	1,966	0.02%	12
33	National Bank of Kuwait Plc	Commercial Bank	1,898	0.02%	8
34	The Access Bank UK Limited	Commercial Bank	1,734	0.02%	9
35	Unity Trust Bank Plc	Commercial Bank	1,623	0.02%	9
36	Hampshire Trust Bank Plc	Commercial Bank	1,499	0.01%	7
37	Bank Leumi (UK) Plc	Commercial Bank	1,488	0.01%	12
38	National Bank of Egypt (UK) Limited	Commercial Bank	1,104	0.01%	9
-	**Sample's Total Assets (2021)**		**6,530,066**	**69.83%**	**Total 417**
-	**UK Banking Sector Total Assets (2021)**		**10,112,755**	**100%**	

Note: Virgin Money UK plc was formerly known as CYBG plc. The company's brands are Clydesdale Bank, Yorkshire Bank, and Virgin Money. NatWest Group plc was previously known as The Royal Bank of Scotland Group plc. Source of data: Bank's annual financial reports, 2021.

4.6 Determinants of bank profitability and variables selection

This section explains the dependent and independent variables selected for the UK banks' profitability analysis. Table 4.2 shows a summary of the research variables.

4.6.1 Profitability measures

Like other businesses, banks' primary aims are maximising revenues (profits) and minimising expenses (costs). Regarding profitability ratios, the values of the financial ratios reflect how well the banks' financial performance is; a high value indicates satisfactory performance. The determinants of profitability in this research will be determined using the profitability ratios as dependent variables, while the bank-specific, industry-specific, and macroeconomic variables are used as independent variables for the UK banks from 2010-2021. The significant and most commonly used profitability ratios in the existing literature are return on equity (ROE), return on asset (ROA), and net interest margin (NIM), and these ratios are standards in banking research (Berger 1995). This research uses the return on average equity (ROAE) and the return on average asset (ROAA) as additional profitability ratios (dependent variables).

4.6.1.1 Dependent variables

- Return on Asset (ROA)

ROA is the first and most used measure of a firm's profitability. It shows how profitable a business is compared to its total assets. It gives a manager, investor, or analyst an idea of how efficiently a firm's administrators use its assets to generate earnings. The metric is typically expressed as a percentage using the company's net profit divided by its total assets. A higher ROA implies a company is more efficient and productive at managing its balance sheet to generate profits, while a lower ROA indicates that an action for improvement is needed. The ratio is calculated as the profit after tax of a bank divided by its total assets.

- Return on Average Asset (ROAA)

ROAA is an extension of the Return on Assets (ROA) ratio. It is calculated as net profit divided by average total assets and is represented as a percentage. Instead of using the total assets at the end of the financial year, ROAA uses a company's opening and closing balance of assets divided by two. Like ROA, the ROAA reflects the capability of a firm's management to generate profits from its assets. This research uses ROAA, in line with ROA, to capture the effect of asset changes during the research period. According to Golin and Delhaise (2013), ROAA has appeared as the critical ratio for evaluating bank profitability as it provides a more accurate picture since average assets will smooth out changes or volatility in assets over an accounting period. Researchers (Petriaa, Caprarub and Ihnatov 2015; Dietrich and Wanzenried 2011; Kosmidou, Tanna and Pasiouras 2008) have used ROAA as a standard measure of bank profitability in their investigations. The ratio is calculated as the profit after tax of a bank divided by its average total assets.

- Return on Equity (ROE)

ROE is a corporation's financial performance measure calculated by dividing its net income by its shareholders' equity (Guillén, Rengifo and Ozsoz 2014). The ROE is the return on net assets as shareholders' equity equals a firm's assets minus its debt. It also reflects the abilities of management to use the shareholders' funds effectively; high ROE indicates that the management uses the shareholders' capital more efficiently. The ROE has been widely used in previous studies on firms' profitability. Some used it as the only representative of profitability (Berger 1995a; Menicucci and Paolucci 2016; Djalilov and Piesse 2016), while other studies used it with other profitability proxies (Short (1979; Smirlock 1985; Molyneux and Thornton 1992; Berger 1995b; Staikouras and Wood 2011; Yao, Haris and Tariq 2018). The ratio is calculated as the profit after tax of a bank divided by its equity.

- Return on Average Equity (ROAE)

ROAE is a modified version of the company profitability indicator return on equity (ROE), in which the denominator "equity" is changed to "average equity". Gigante (2013) states that the average is an approximation that does not reflect any instability during reporting periods; it is implicitly assumed that fluctuations are relatively smooth. Commonly, the ROAE refers to a firm's performance over a fiscal year, so the average equity is usually calculated as the sum of the equity value at the opening and the end of the year divided by two. In the literature, ROAE is used by researchers (Kosmidou, Tanna and Pasiouras 2008; Dietrich and Wanzenried 2011; Petriaa, Caprarub and Ihnatov 2015) as a standard measure of bank profitability in their investigations. The ratio is calculated as the profit after tax of a bank divided by its average equity.

- Net Interest Margin (NIM)

NIM is a profitability indicator focusing on the profit earned from interest activities. Dietrich and Wanzenried (2011) state that NIM compares a financial company's net interest income from its credit products, such as loans and mortgages, with the outgoing interest it gives to savings accounts and certificates of deposit holders. It is calculated by dividing the net interest income by total assets. NIM helps investors decide whether to invest in a financial services company by giving visibility to their interest earnings versus interest costs. A higher NIM ratio indicates that the interest return is worthy and the investment is valuable. The net interest margin ratio has been used in many bank profitability investigations (Tanna and Pasiouras 2008; Kosmidou, Dietrich and Wanzenried 2011; Tan and Floros 2012; Tan 2016; Yao, Haris, and Tariq 2018; Le and Ngo 2020). The ratio is calculated as the net interest income of a bank divided by its average earning assets.

4.6.2 Determinants of bank profitability

In this part, the selected determinants of bank profitability are defined by splitting them into three diverse groups of independent variables: bank-specific variables (internal factors), industry-specific variables, and macroeconomic variables (external factors), while questioning their expected effects on the UK banks profitability in conformity with the estimates derived from the empirical studies conducted in developed and developing economies.

4.6.2.1 Independent variables definitions

- Bank-specific factors (internal)

- Bank size (SIZE)

The impact of the size on the banks' profitability is intensely discussed among researchers, and it significantly appears in most studies that have been directed to investigate the banks' performance.

Existing academic research and official sector documents often focus on balance sheet totals when evaluating the size and significance of banks and the banking system (Schildbach 2017). Total assets, total revenues, market capitalisation, equity capital, risk-weighted assets, net income, number of branches, and number of customers could measure the size of banks. To date, total assets remain an indicator regulators, bankers, financial supervisors, and academics use most often to measure banks' size.

The influence of size is variant in the literature. Authors such as Short (1979), Smirlock (1985), Bikker and Hu (2002), Pasiouras et al. (2007) and Guillen et al. (2014) find that size has a positive impact on bank performance since a significant size decreases costs, and this due to the economies of scale that it entails as banks of significant size can raise capital at a lower cost. For others (Stiroh and Rumble 2006; Kasman 2010; Dietrich and Wanzenried 2011), the size negatively affects bank performance. Their empirical results show an adverse effect of the size, and they stress that the larger the bank is, the harder it will be managed.

In line with the existing literature, this research uses size, measured by banks' total assets, as a bank-specific variable to evaluate its impact on UK banks' profitability. The natural logarithm of the banks' total assets is used to ease the data. There is no prior expectation of the impact of a bank’s size on profitability, as the literature review supports both sides.

- Liquidity coverage ratio (LCR)

The Liquidity Coverage Ratio (LCR) is a prominent regulatory measure designed to assess financial institutions' short-term liquidity risk exposure, particularly banks. The Basel Committee on Banking Supervision (2010) introduced the ratio in response to the 2007/09 global financial crisis. The LCR aims to ensure that banks maintain sufficient high-quality liquid assets to withstand a significant stress event lasting 30 days. The ratio was introduced as part of Basel III regulatory reforms to address the liquidity risk vulnerabilities exposed during the financial crisis. Banks must maintain an adequate stock of liquid assets to meet short-term obligations during a stress scenario. The primary objective of the LCR is to ensure that banks possess a robust buffer of high-quality liquid assets to cover potential liquidity outflows during 30 days of stress. By doing so, regulators aim to minimize the risk of bank runs and systemic crises, enhancing the financial system's stability (Hong, Huang and Wu, 2014).

The regulatory Liquidity Coverage Ratio (LCR) evaluates a bank's high-quality liquid asset holdings concerning its anticipated net cash withdrawals over a 30-day stress period. The stock of High-Quality Liquid Assets (HQLA) and Net Cash Outflows make up this component. Although adhering to the LCR can make banks more resilient to liquidity shocks, it also reduces their ability to make money. Holding liquid assets while maximizing profits is a delicate balancing act for financial organizations. Regulators can evaluate a bank's exposure to liquidity risk and resilience to challenging situations with the support of regular reporting of LCRs. Penalties and regulatory measures may follow non-compliance. The LCR fosters diversified funding sources, encourages good liquidity risk management techniques, and creates backup plans for unexpected liquidity shortages (Sidhu et al., 2022).

The results of investigating the impact of LCR on profitability vary. Applying a panel data technique of random effects estimation and generalized method of moments (GMM), Muriithi and Waweru (2017) found that LCR, as a liquidity risk measure, does not significantly influence the banks' financial performance both in the long run and short run. However, the overall effect was that liquidity risk hurts financial performance. A Study by Toby (2011) shows a negative association between bank liquidity and profitability. The results are attributed to banks holding liquid assets as an obligation to the requirements assessed by the authorities. Also, holding money for these purposes may lead to low bank profitability as low returns are anticipated. They argue that when banks have inadequate liquidity, they cannot obtain satisfactory funds by increasing liabilities or converting assets promptly at a reasonable cost, thus affecting profitability. There is also opportunity cost incurred by liquid assets, which has a negative effect on bank profitability. However, these results differ from studies of Said and Tumin (2011) and Akhtar And Sadaqat (2011), that liquidity risk positively affects bank profitability.

This research used LCR as a Basel III regulatory ratio to examine its association with bank profitability. A negative effect of LCR on bank profitability is expected.

- Net Stable funding ratio (NSFR)

The NSFR is another quantitative liquidity ratio introduced in line with the LCR by the Basel Committee on Banking Supervision (2010). The ratio manages the funding risk by influencing banks to recourse to more stable and safe funding sources (Sidhu et al., 2022).

Enforcing this new long-term liquidity ratio directs banks to rethink their financial strategies, which can henceforth influence their financial performance. To capitulate with the NSFR, a bank needs to restructure its balance sheet by extending the maturity of wholesale funding and holding more high-quality liquid assets. These changes would prevent bank failures and promote the financial sector's stability and resilience (King 2013).

The existing literature shows that some studies have been directed to examine the impact of NSFR on bank performance. Dang (2021) investigates the impact of NSFR on the performance of Vietnamese banks from 2007–2018. The findings indicate that the higher NSFR levels not only have a favourable effect on the accounting ratios, return on assets (ROA) and return on equity (ROE) but also lead to an increase in the banks' NIM by lowering funding costs. These findings agree with those of Khan et al. (2015), who demonstrate an improvement in the NIM of the US commercial banks, as the fund providers prefer banks with satisfactory liquidity. Further, Said (2014) documents that compliance with the NSFR augments bank performance in response to the enlarged stock of stable and safe funding sources. Regardless, another strand of literature indicates that this profitability improvement due to higher liquidity is unstable. Beyond this point, as more liquidity is infused into the system, the higher cost associated with these relatively stable funding sources starts to outweigh their marginal benefits, thus influencing the banks' financial performance (Le et al., 2020).

The NSFR is calculated by dividing an institution's available stable funding (ASF) by its required stable funding (RSF). ASF encompasses the amount of stable liabilities and capital that supports the bank's assets, while RSF evaluates the liquidity characteristics of the bank's assets. This research used NSFR as a Basel III regulatory ratio to examine its association with bank profitability. A positive effect of this ratio on bank profitability is expected.

- Financing gap ratio (FGR)

The FGR was introduced by Saunders and Cornett in 2007 (Saunders and Cornett, 2018). They expressed that the liquidity risk measure is determined based on the financial gap. Bank managers mainly assume core deposits as a stable source of funds to finance the banking loan supply. Generally, core deposits are regarded as loan resources with the least cost. A financial gap is the difference between a loan and a bank's core deposits.

The bank should fill the gap with cash funds by selling cash assets and borrowing from the money market if the gap is positive. Therefore, the financial gap can be estimated by subtracting the borrowed funds from the cash assets. After selling its cash assets, this financial gap represents the bank's financial needs. Banks are more exposed to liquidity risk when the economy stagnates and the financial market increasingly demands cash funds (Otieno, Nyagol and Onditi, 2016).

The FGR is calculated by dividing the financial gap (loans minus deposits) by its total assets. Banks with higher FGR are expected to use much of their cash, sell liquid assets and depend on non-deposit funding to compensate for the financial gap, increasing the funding cost and reducing profitability. If markets for deposits are reasonably positive, then greater liquidity will be negatively associated with financial performance measures. This research uses FGR to examine its association with bank profitability. A negative effect of FGR on bank profitability is expected.

- Loan growth (LOANGR)

Loans are considered the primary source of bank income; hence, loan growth (LOANGR) is expected to generate higher profitability. The LOANGR is measured by taking the annual percentage change in the bank's total outstanding loans. The LOANGR is used widely in the existing literature, including early and recent studies, which provide mixed results.

Studies by Molyneux and Thornton (1992) and Miller and Noulas (1997) report a negative association between loan growth and bank profitability. Their findings suggest that excessive loan growth may lead to more significant risks, reducing bank profitability. In contrast, Al-Khouri and Arouri (2016) show the opposite results, where loan growth positively affects profitability. They argue that profitable banks are more likely to raise credit since they can attract more funds. This positive association align with the results of Le (2020), who finds a positive relationship between loan growth and bank profitability, proxied by the return on equity (ROE).

Dang (2019) reports a significant positive impact of loan growth on ROA and ROE. Their results imply that the bank's lending expansion generally causes better profitability, both in the short term and long term. These findings contradict other studies (Foos, Norden and Weber, 2010; Fahlenbrach, Prilmeier and Stulz, 2016; Paul, Kilungu and Andrew, 2016). This research uses LOANGR to investigate its association with bank profitability. A negative effect of LOANGR on bank profitability is expected.

- Non-performing loan ratio (NPL)

Non-performing loans (NPL) are loans that experience repayment problems or are often called bad loans at banks. NPL affects bank lending where there are loans with bad loan quality, often called non-performing loans. If there is an issue with non-performing loans, it will indirectly be detrimental to those who own the funds. The provision of a loan facility carries a risk of default; as a result, the loan cannot be collected, resulting in losses that the bank must bear (Ciukaj and Kil, 2020).

The non-performing loan ratio is a crucial metric that lenders use to assess the health of their loan portfolio. The NPL ratio is calculated by dividing the total value of non-performing loans by the total value of outstanding loans, and it is expressed as a percentage. A high non-performing loan ratio can indicate that a lender is experiencing financial stress and may be unable to meet its obligations to its borrowers. Therefore, lenders must closely monitor this ratio and appropriately address potential issues (Ozili, 2019).

Banks and financial institutions closely monitor their NPL ratio as part of their risk management and regulatory compliance efforts. Regulatory bodies often set limits on the acceptable level of NPL ratios, and exceeding these limits might lead to regulatory actions or increased scrutiny. A decreasing NPL ratio can be seen as a positive sign, as it indicates improving loan quality and credit management.

It is worth noting that the NPL ratio can vary across different banks, financial sectors, and economies. It is an essential metric for assessing the overall health of a financial institution's loan portfolio and its ability to manage credit risk effectively. This research uses NPL to investigate its association with bank profitability. A negative effect of NPL on bank profitability is expected.

- Effective tax rate (ETR)

A company's effective tax rate (ETR) is a percentage of the tax rate paid by that company. It is calculated or estimated based on financial information generated by the institution, so it is a form of calculation of corporate tax rates. ETR is the ratio of taxes a corporation pays based on its total income before accounting for income tax. It can determine how much percentage change pays actual taxes to the commercial profit obtained by the corporation.

Dietrich and Wanzenried (2011) define ETR as taxes divided by before-tax profits, reflecting the direct taxes paid by the banks (primarily corporate income taxes). They also mention that when the effective tax rate is high, banks are expected to shift a significant fraction of their tax obligation onto their depositors and borrowers of fee-generating services. This would shield those banks from the total influence of the higher tax commitment, but it would not eliminate the impact completely.

Using this ratio in this research as a bank-specific variable provides an opportunity to see whether the effective tax rates affect the profitability of UK commercial banks. Thus, agreeing with the results of Demirguc-Kunt and Huizinga (1999), it is expected that the effective tax rate has a negative effect on bank profitability.

- Loan specialisation ratio (LOAN)

The loan ratio measures the banks' loans outstanding as a percentage of their total assets. It indicates the liquidity that reflects credit and shows banks' ability to meet the credit demand with total assets owned (Sufian and Habibullah 2010; Sufian 2011). The ratio is used to demonstrate the ability of banks to meet the demand for loans by using their owned total assets. A higher loan ratio means a better credit performance level because the loan is a more significant component in the total structure of the assets. However, it negatively affects liquidity since a higher ratio value means existing funds are widely used for credit funding and less for short-term liabilities. According to Olson and Zoubi (2011), the bank-specific variable loan ratio is sometimes used to measure the liquidity risk or asset utilization ratio. Since loans provide the highest return on a bank's asset, loans should positively influence profitability if banks are not taking on an unacceptable level of risk.

This research uses the loan ratio to capture its impact on UK banks' profitability. The ratio is computed by dividing the net loans by the bank's total assets. Since loans are the top financial product banks offer, the loan ratio is expected to impact banks' profitability positively.

- Deposit ratio (DEP)

Deposits can be seen as the primary sources of funds for banks and possibly are the cheapest as banks generally pay less interest to their depositors than they pay to their lenders. More deposits for banks mean more loan opportunities will be provided to customers and then generate further profits. So, it could be argued that higher upward deposits would develop the bank's business and create more profits. The bank's operating efficiency influences this association in transforming the deposit liabilities into income-earning assets. Customer deposits are supposed to influence banks' performance if there is sufficient market loan demand. Lee and Hsieh (2013) argue that increasing customer deposits indicates a growth in the funds available for different profitable opportunities such as lending and investments; consequently, customer deposits are positively associated with banks' profitability. Saeed (2014), however, argues that if a bank cannot release money through loans, its profitability level decreases due to paying interest to depositors on their fixed, time, or term deposits.

In a study directed to investigate the profitability of 73 UK commercial banks before, during, and after the financial crisis of 2008, Saeed (2014) found a positive effect of deposits on ROA and ROE. The deposits ratio represents customer deposits and can be calculated by dividing total customer deposits by the bank's total assets. As deposits are another source of income, this research expects that banks' profitability is positively linked to customer deposits.

- Operating efficiency (OE)

Operating efficiency indicates a company's management efficiency level in running the business. The cost and revenue are the two most considered when evaluating an existing business or entering a new market. It could be the quickest way to have an initial idea about the business's performance before going into deep financial analysis. In this matter, to gauge the organisation's operational efficiency, the ratio of cost to income is used to measure operational efficiency.

Hess and Francis (2004) define the cost-income ratio as the non-interest expenses divided by the sum of net interest income and non-interest income, where non-interest expense usually excludes bad debt and tax expenses. This measure has intuitive appeal and is thus often called the efficiency ratio. They also argue that this ratio is commonly considered an important benchmark, specifically among publicly traded banks, as it is the focus of many bank equity analysts when measuring relative efficiency in the sector.

Banks use this ratio for tracking the movements of their costs versus their income for the same period. As the ratio depends on cost and income figures, banks could lower the ratio's value by either increasing their operating revenues or decreasing their operating expenses. A prohibitive cost-to-income ratio may indicate that a bank is not efficiently managed or that a high competition level exists in the banking industry.

The cost-to-income ratio is used chiefly to determine banks' profitability and represents the efficiency at which the banks are being run. A lower ratio indicates more banks' profitability. This research uses the efficiency ratio to capture its impact on UK banks' profitability. The ratio is computed in line with the existing literature by dividing the operating expenses by the operating revenues of the UK banks. A negative effect of this ratio on bank profitability is expected.

- Industry-specific (external)

- Market concentration (MC)

Market Concentration refers to some businesses and their separate shares of the total production in a market. Various forces, including barriers to entry and existing competition, influence it. From a theoretical and practical perspective, market concentration is strongly associated with market competitiveness and, consequently, is essential to various antitrust agencies when considering offered mergers and other regulatory issues. The market concentration ratio estimates the concentration of the top companies in a market through different metrics such as revenues, assets, active users, or other appropriate indicators. It allows users to determine the market structure they observe, from perfect competition to a monopolistic, monopoly or oligopolistic market structure. According to Staikouras and Wood (2011), the most used market concentration measures are the Herfindahl–Hirschman Index (HHI) and the concentration ratio. The HHI is calculated by taking the sum of the squares of the firms' market shares in a relevant market, while the firm concentration ratio is measured as the sum of the market shares of the top 3, 4 or 5 firms with the most significant market shares in a market. A firm's market share is calculated based on the value of total assets.

Several studies have been directed to investigate the effect of concentration on bank profitability, and their results show different indications. In a study investigating the performance of banks in twelve countries in Europe, North America and Australia, Bourke (1989) found concentration to be moderately and positively related to pre-tax return on assets. In contrast, Staikouras and Wood (2011) found a significant but negative association between concentration ratio and bank profitability.

Since the term "Big Four" is used when referring to the UK banking sector, this research measures the concentration of the UK banking sector by using the concentration ratio for the big four UK banks in terms of total assets, depending on data availability. Based on the data collected for this research, these banks held 57.65% of the UK banking sector in total assets in 2021[9]. The concentration ratio and the banks' market share variables are calculated based on the size of the banking sector's total assets. The bank’s market share is the bank's total assets divided by the total assets of the UK banking sector. A negative effect of the concentration ratio on bank profitability is expected.

[9] The 57.65% is the sum of market shares of HSBC Holdings Plc, Barclays Bank Plc, Lloyds Banking Group Plc, NatWest Group Plc in terms of total assets in 2021.

- Ownership structure (PC)

The banks in this research sample are classified into public and private banks. This classification investigates the impact of being a public or private bank on bank profitability. The general difference between the two types is that a public bank is listed on a stock exchange, while a private bank is not. A bank becomes publicly quoted by making an initial public offering of shares in the bank. This is a way to help boost capital and provide investors and the bank with an effective way to create wealth.

Several authors (Barth, Caprio and Levine 2004; Iannotta, Nocera and Sironi 2007; Micco, Panizza and Yañez 2007; Cornet et al. 2010; Dietrich and Wanzenried 2014) have investigated the bank's ownership structure (Public or Private), and they end up with different statements and results. Some authors see that banks' performance is linked to the banks' policy and management, and others link the performance to the existence of control, power, and political issues. Barth, Caprio and Levine (2004), Iannotta, Nocera and Sironi (2007) and Cornet et al. (2010) argue that public banks are less potent than private banks. They argue that, compared to private banks, public banks grant riskier loans, which leads to higher credit risk and a lower quality of assets, and then face solvency ratios. Cornet et al. (2010) state that the difference in performance between private and public banks is observed in countries where power is highly involved in their banking systems. Also, the banks' performance is affected by political corruption. Micco, Panizza and Yañez (2007) argue that bank control impacts performance. However, this association is mainly apparent in developing economies where the nationalized banks have weak performances, low margins, and high overheads, while in developed economies, this association seems much less marked. In a study of the determinants of banking profitability of 118 countries during 1998-2012, Dietrich and Wanzenried (2014) found a negative and significant influence of privatization on banking performance.

This research uses ownership structure variables at a public and private level to overview the two types of banks operating in the UK banking sector. The research sample consists of 12 publicly quoted banks and 38 private banks. A dummy variable equals 1 for privately owned banks and 0 otherwise. This helps to stand on the effect of ownership structure on banks' profitability by comparing the results between banks at a public and private level. A positive effect of publicly quoted levels on profitability is expected.

- Ownership status (DB)

The ownership status of banks can be measured at a domestic and foreign level. The distinction between the two is that banks operating in multiple countries are called foreign-owned banks, while banks within a country's boundaries are called domestic-owned banks. Another way to define the two types is that banks with registered offices in the UK and operating within the UK are domestic-owned banks, while banks with registered offices abroad and operating in the UK are called foreign-owned banks. The domestic bank must stick to the country's local laws that it is registered with, while the foreign bank must comply with the local laws of the county where its headquarters is and the country's laws that it operates within.

The influence of introducing foreign banks in the local banking sector has been a debated issue in finance. Levine (1997) and Buch and Golder (2001) argue that foreign-owned banks may enhance the quality and availability of financial services in the domestic financial sector through competition in terms of technological development. He also argues that foreign-owned banks facilitate the development of supervision and banking regulations, allowing access to the international capital market.

Based on the existing literature, the results of investigating the effect of being a domestic or foreign bank on its profitability differ. Buch and Golder (2001) assume that foreign banks can cause the failure of less competitive domestic banks because they might displace local lending. However, Kosmidou et al. (2006) state that domestic banks perform better than foreign ones. This statement aligns with other investigations by (Sathye 2001; De Young and Noll 1996), which show that foreign banks are less profitable than domestic banks. Bouzgarrou, Jouida and Louhichi (2018) state that the outperformance of foreign banks can be explained by the fact that they are experienced in trade finance and foreign exchange business. This experience facilitates them to supply sophisticated banking services to their clients, boosting their profitability. To estimate the cost-benefit frontier for comparing the efficiency of domestic and foreign banks, Berger et al. (2000) conclude that foreign banks are only less efficient in cost-benefit than domestic banks in three European countries: the UK, France, and Germany. He explains these results through cultural differences, regulation, language, and other explicit and implicit barriers.

This research uses ownership status to overview the two types of banks operating in the UK banking sector. The research sample consists of 26 domestic banks and 24 foreign banks. A dummy variable equals one if the bank is domestically owned and zero if otherwise is used. This helps to stand on the effect of ownership status on banks' profitability by comparing the results between banks at domestic and foreign levels. A positive effect of the domestic-owned level on bank profitability is expected.

- Macroeconomics variables (external)

- Inflation rate (INF)

The inflation rate indicates the rate of changes in the price of any commodity. In other words, it measures how much the prices of services and goods have increased over time. The price rise expressed as a percentage, shows that a currency unit buys less than in prior periods. Inflation is also expressed as a decrease in the purchasing power of a given currency over time.

To maintain the stability of inflation and help businesses and people plan, the UK government set the Bank of England an inflation target of 2%. The Office for National Statistics (ONS) gathers around 180,000 prices of about 700 items in the UK. This shopping basket works out the Consumer Prices

Index (CPI), which measures the inflation the Bank of England targets (Bank of England, 2022). Regarding the UK economy, the ONS statistics show that the annual inflation rate fluctuated during 2010-2021 (the period of this research) with an average of 3.03%. The rate was 4.6% in 2010 compared to 4.1% in 2021.

In most studies that used inflation as a macroeconomic variable, inflation has an inverse relationship to profitability because an increase in inflation means lowering banks' profitability due to higher prices. Investigations (Bourke (1989; Dietrich and Wanzenried 2011; Tan and Floros 2012; Petria, Caprarub and Ihnatov 2015; Tan 2016 Djalilov and Piesse 2016; Yao, Haris and Tariq 2018; Homaidi et al. 2020; Le and Ngo 2020; Kumar, Thrikawala and Acharya 2021; O'Connell 2022) found negative relationship between inflation and profitability. The inverse relationship is primarily based on the capability of banks to predict inflation occurrence. If the banks succeed in anticipating the inflation rate and its occurrence, they can devise proper strategies for dealing with this situation.

Although the initial perspective indicates an inverse relationship between inflation and profitability, the effect level could vary between developed and developing economies, depending on the inflation rate and the sensitivity of sectors to it. However, a high inflation rate is associated with higher costs and income. Inflation could significantly affect profitability if a bank's income increases more rapidly than its costs. This research uses the inflation rate as a macroeconomic variable to investigate its impact on UK banks' profitability. There is no prior expectation of the impact of the inflation rate on bank profitability.

- Gross domestic product growth rate (GDPG)

Gross domestic product (GDP) is one of the economic indicators of development. It is the total economic or market value of all the finished goods and services produced within a country’s borders in a specific period. As an overall measure of domestic production, it is a comprehensive scorecard of a given country’s economic health. GDP is typically calculated annually, and it is sometimes calculated quarterly (Office for National Statistics 2022b)

The GDP growth rate approximates the year-over-year or quarterly change in a country’s economic outputs to estimate how quickly an economy grows. GDP growth is popular with economic policymakers because it is associated with crucial policy targets such as inflation and unemployment rates. The changes in GDP growth decide what decisions a central bank could take. When GDP growth rates accelerate, the central bank may seek to raise interest rates while, oppositely, a shrinking or negative GDP growth rate indicates that rates should be lowered and that stimulus may be necessary.

According to Bouzgarrou, Jouida and Louhichi (2018), GDP positively affects bank profitability. They argue that higher economic growth leads to more demand for interest and non-interest activities, improving banks' profitability. Their justification is that the default risk is lower in upturns than in downturns.

As presented in chapter three, the literature on bank profitability, the existing literature (Demirguc-Kunt and Huizinga, 1999; Athanasoglou, Brissimis, and Delis, 2008) shows that the investigations' results found a positive effect of GDP on profitability. Due to a lack of previous studies that have been conducted to investigate the determinants of the UK banks' profitability in an individual country rather than cross-country, this research uses the UK annual GDP growth rate as a macroeconomic variable. Consequently, as the demand for lending increases during cyclical upswings, this research expects that GDP growth positively affects bank profitability.

- Covid-19 (COV)

The Covid-19 pandemic has caused global collapse, inactivity, and loss of jobs that are exceptional in scale and speed. Most of the small and large businesses across every country globally have had to close their doors to customers and workers. The sharp decrease in businesses' revenues and households' incomes resulted in the first global recession, presenting the global financial system with the most significant stress event since the 2007/09 GFC (Demirgüç-Kunt, Pedraza and Ruiz-Ortega 2021).

The crises vary in their effect levels based on the sector they affect and their separation (locally or internationally). Over a decade ago, the financial system, mainly banks, was the epicentre of the global financial crisis, its fundamental cause and trigger. In contrast, the Covid-19 pandemic is the epicentre of the crisis this time, while the banking sector is seen as a part of the solution rather than the problem. Regarding the UK, the response of the Bank of England to the pandemic was clear and compelling. The BoE was performed to save jobs and support the UK economy through measures and determinations. According to the Bank of England (2020a), in March 2020, the BoE cut its interest rate (Bank Rate). The cut in the Bank Rate offered the UK banks and building societies long-term funding at interest rates of 0.1%. This results in cheaper loans for businesses and households. That reduced the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households.

This research uses Covid-19 as a macroeconomic variable. A dummy variable equal to 1 for the years of the Covid-19 pandemic and 0 otherwise is used. A negative effect of the Covid-19 pandemic on bank profitability is expected.

Table 4.2: Variables used, descriptions, and their expected effect on banks' profitability.

Variables	Abv	Description	Measures	Expected Signs
Dependent Variables				
	ROA	Return on assets	Net income / total assets (%).	
	ROAA	Return on average assets	Net income / average total assets (%).	
	ROE	Return on equity	Net income / total equity (%).	
	ROAE	Return on average equity	Net income / average total equity (%).	
	NIM	Net interest margin	Net interest income / average earning assets (%).	
Independent Variables				
	SIZE	Bank size	Bank's natural logarithm total assets (£m).	+/-
	NPL	Non-performing loan ratio	Bank's total value of non-performing loans by its total value of outstanding loans.	-
	OE	Operating efficiency	Operating expenses are divided by the operating revenues.	-
	LCR	Liquidity coverage ratio	Bank's stock of high-quality liquid assets divided by Total net cash outflows over the next 30 days.	-
	NSFR	Net stable funding ratio	Bank's available stable funding (ASF) is divided by its required stable funding.	+
	FGR	Financing gap ratio	Net loans minus total deposits divided by total assets.	+
	LOAN	Loan specialisation ratio	Net loans are divided by total assets.	+
	LOANGR	Laon growth ratio	The growth in the bank's gross loan as a percentage.	+
	DEP	Deposits ratio	Customer deposits are divided by total assets.	+
	PC	Ownership structure	The dummy variable equals 1 for publicly quoted banks and 0 otherwise.	+
	DB	Ownership status	The dummy variable equals 1 for domestic banks and 0 otherwise.	+
	ETR	Effective tax rate	Total taxes paid divided by profit before tax.	-
	MC	Market concentration	The sum of the market share for the most significant UK four banks.	-
	INF	Inflation rate	UK Inflation rate (annual %).	+/-
	GDPGR	GDP growth rate	The growth in GDP of the UK (annual %).	+
	COV	Covid-19	The dummy variable equals 1 for the years of (Covid-19) 2020-2021 and 0 otherwise.	-

4.7 Econometric specification of the models

4.7.1 Profitability model

To investigate the relationship between the UK bank profitability and its determinants, data is analysed by applying a linear regression model in line with (Goddard, Molyneux and Wilson 2004; Athanasoglou, Brissimis and Delis 2008; Tan 2016; Djalilov and Piesse 2016; Yao, Haris and Tariq 2018; Homaidi et al. 2020; Le and Ngo 2020), who proved that the linear analysis produced results as interesting as from any other type of functions. The general model to be estimated is of the following linear form.

$$\Pi_{it} = c + \sum_{j=1}^{J} \beta_j X_{it}^{j} + \sum_{l=1}^{L} \beta_l X_{it}^{l} + \sum_{m=1}^{M} \beta_m X_{it}^{m} + \varepsilon_{it} \text{ , where } \varepsilon_{it} = v_i + u_{it} \qquad \text{Eq. (4.1)}$$

Where Π_{it} is the profitability of bank i at time t, with i = 1, ..., N, t = 1, ..., T, c is a constant term, X_{it}'s are the explanatory variables and ε_{it} the disturbance, with v_i the unobserved bank-specific effect and u_{it} the idiosyncratic error. The X_{it}'s are grouped into bank-specific X_{it}^{j}, industry-specific X_{it}^{l}, and macroeconomic variables X_{it}^{m} .

The empirical studies examining the determinants of banks' profitability assume that the former tends to persist over time. These studies identify an endogeneity problem when observations of the explanatory variables are not entirely independent of the past value of the dependent variable. Hence, they included banks' profitability as a lagged variable amongst the regressors. According to (Berger et al. 2000; Goddard, Molyneux and Wilson 2004; Athanasoglou, Brissimis and Delis 2008; Djalilov and Piesse 2016; Le and Ngo 2020; Kumar, Thrikawala and Acharya 2021; O'Connell 2022), banks' profit shows a trend of persisting over time. Therefore, this reflects impediments to market competition, informational opacity, and sensitivity to regional or macroeconomic shocks to the extent that these are serially associated. For this reason, a dynamic specification of the model is adopted by including a lagged dependent variable ($\Pi_{i,t-1}$) along with the regressors.

This research uses a methodology based on a dynamic panel model to investigate the impact of bank-specific, industry-specific, and macroeconomic variables on UK banks' profitability. A model specification is needed when a lagged dependent variable is comprised among the regressors.

The equation (4.1) with lagged profitability is as follows.

$$\Pi_{it} = c + \alpha\Pi_{i,t-1} + \sum_{j=1}^{J} \beta_j X_{it-1}^{j} + \sum_{l=1}^{L} \beta_l X_{it}^{l} + \sum_{m=1}^{M} \beta_m X_{it}^{m} + \varepsilon_{it} \qquad \text{Eq. (4.2)}$$

Where $\Pi_{i,t-1}$ is the one-period lagged profitability, and α is the equilibrium adjustment speed. Values of α between 0 and 1 indicate that profits persist but will ultimately return to their average level. If the value of α is close to 0, it tells that the industry is relatively competitive, while if the value is close to 1, it implies a less competitive structure (Berger et al. 2000; Goddard, Molyneux and Wilson 2004;

Athanasoglou, Brissimis and Delis 2008; Djalilov and Piesse 2016). The X^{j}_{it-1} is the bank-specific variables lagged by one period.

This research has five dependent variables representing the profitability of banks, measured by ROA, ROAA, ROE, ROAE, and NIM. The model is run for each dependent variable, and each dependent variable is a function of the same 22 explanatory variables, including the lagged dependent variable.

4.7.2 The standard estimators

Baltagi (2021) argues that significant economic associations are naturally dynamic, and the panel data have the advantage of allowing the researcher to understand the adjustment dynamics. This research uses panel data to investigate the relationship between the dependent and independent variables by using the Ordinary Least Square (OLS), Fixed Effects (FE), and the Generalised Method of Moments (GMM) approaches. A brief explanation of the three estimators is given in the following sections. More explanation and comparison between the estimators will be addressed in Chapter 5.

4.7.2.1 Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators

The OLS is a standard technique for estimating coefficients of linear regression equations (simple or multiple), defining the association between independent quantitative and dependent variables. The OLS stands for the minimum squares error (SSE). Maximum likelihood and the Generalised Method of Moments estimator are alternative approaches to OLS. The OLS method minimises the prediction error between the predicted and actual values. The estimator assumes that observations are independent, variance is homogeneous, and residuals follow a normal distribution. Minimising the sum of squared errors instead of the sum of errors is because sometimes they can be negative or positive, and they could sum up to a near-null value (Hill, Griffiths and Lim 2018).

Hill, Griffiths and Lim (2018) define the FE model as a statistical model in which the model parameters are fixed or non-random quantities. This contrasts with random-effects and mixed models in which all or some of the model parameters are random variables. In econometrics, a fixed-effects model refers to a regression model in which the group means are fixed (non-random) as opposed to a random-effects model in which the group means are a random sample from a population. Typically, data can be grouped according to several experimental factors. The group means could be modelled as fixed or random effects for each grouping. In a fixed-effects model, each group mean is a group-specific fixed quantity. The fixed-effects model represents the subject-specific means in panel data where longitudinal observations exist for the same subject. In panel data analysis, the term fixed effects estimator (also known as the within estimator) refers to an estimator for the coefficients in the regression model, including those fixed effects (one time-invariant intercept for each subject).

The standard estimators are applied to dynamic panel data models that need to account for cross-sectional fixed effects and exhibit the following properties. The pooled OLS estimator shows dynamic panel bias and is inconsistent when T is small, even if N is large. The coefficient of the lagged dependent variable is upward biased when pooled OLS is applied to a dynamic panel model when T is small. The fixed-effects (FE) estimator is also biased and inconsistent (as N increases) for small T when using dynamic panel models. According to Roodman (2009), the bias and inconsistency of the fixed-effects estimator vanish as T increases. Nevertheless, this estimator can still have a substantial bias (20%) when T = 30. The coefficient of the lagged dependent variable is downward biased when the FE is used to estimate dynamic panel models with small T. Since these two estimators are biased in opposite directions for the lagged dependent variable's coefficient, both estimators are applied to indicate a range that the lagged dependent variable's population coefficient is expected to be within. As these estimators have a sampling distribution that may offset the bias of one or both estimators, the population coefficient may not fall in this range (Roodman 2009).

4.7.3 The Generalized Method of Moments (GMM)

The Dynamic GMM model widely exists among researchers who directed their studies using panel data. The model was presented in 1991 by Manuel Arellano and Stephen to address specific endogeneity problems. According to Baltagi (2021), the Arellano–Bond estimator is a generalized method of moments estimator used to gauge dynamic panel data models.

This research applies the difference and system GMM dynamic panel estimators that are consistent as N (though not T) tend to infinity. Since the latter is expected to be more appropriate for modelling (stationary) near unit root processes than the former (Roodman 2009), considering both helps ensure appropriate modelling of this research's data regardless of the data generation process. For both difference and system GMM methods, the one-step estimator (with coefficient standard errors that are robust to autocorrelation and heteroscedasticity) and the two-step estimator (with Windmeijer, 2005, small sample corrected robust coefficient standard errors) will be applied. Given that one form of GMM estimator is not unambiguously superior to the others, all four to assess their relative performance are considered. While the two-step coefficient estimator is asymptotically efficient and superior to the one-step estimator, the two-step coefficient standard errors are biased downwards. However, the Windmeijer (2005) correction dramatically reduces this problem (Roodman 2009).

All regressors except for the lagged dependent variable are assumed to be strictly exogenous because they are industry-specific or macroeconomic covariates unlikely to be significantly influenced by individual banks or entered lagged by one period. The appropriate lagged dependent variable will be used as the basis for the GMM-style instruments. Since the number of GMM-style instruments equals the number of time-series observations (T), the GMM-style instruments collapsed into one will be used to avoid having so many instruments that the instrument equation is overfitted and does not remove the endogeneity of the lagged dependent variable. Roodman (2009) states that using collapsed GMM-style instruments causes a slight loss of estimation efficiency. However, in some instances, the GMM-style instruments are not collapsed into one to ensure the equations are over-identified.

Hansen's J-statistic will assess instruments' exogeneity, allowing for heteroscedastic and autocorrelated residuals. However, as the number of instruments increases, the test's power falls such that it becomes biased towards accepting the null of exogenous instruments. To avoid unduly reducing the power of this test and to ensure the instrumented equation is not overfitted, it is essential not to use too many instruments. Roodman (2009) suggests that there are too many instruments if there are more instruments than cross-sectional units in the panel. Ensuring that the number of instruments is lower than the number of cross-sections for all models estimated by GMM is vital.

4.8 Data analysis method

The nature of the data used for research plays an essential role in choosing the data analysis method. As this research is quantitative, the method of data analysis adopted is quantitative. According to Saunders, Lewis and Thornhill (2015), quantitative analysis is any economic, business, or financial analysis that strives to explain or predict behaviour or events through mathematical measurements, calculations, statistical modelling, and research. It is used for several reasons, including measurements, performance evaluation, or valuation of financial instruments.

4.9 Summary

This chapter explains the methodology and method of investigating the determinants of UK banks' profitability. The chapter is organised into sections presenting the research questions and the research hypothesis. Then, it presented the research philosophy, approach, data type, and collection method. Furthermore, it presented the research period, sample, and data. It also provided a detailed explanation of the determinants of bank profitability and variable selection. This section has two subsections for the profitability measures (dependent variables) and the determinants of banks' profitability (independent variables). The determinants of banks' profitability were classified into bank-specific, industry-specific, and macroeconomic factors. The Ordinary Least Squares (OLS) and Fixed Effects (FE) have been presented in the section on standard estimators. The chapter also presented the econometric specification of the dynamic panel system GMM model used for analysing the data. Lastly, it presented the data analysis method. This chapter included two comprehensives, Table 4.1 and Table 4.2, presenting valuable information. The sample of the banks used in the research, including their total assets, market shares compared to the whole UK banking sector and their specialisations, and the number of observations for each bank, was presented in Table 4.1. A summary of the dependent and independent variables, their descriptions, and their expected effect on banks' profitability was presented in Table 4.2

Chapter 5: Results and discussion on bank profitability

5.1 Introduction

This research seeks to identify the determinants of UK banks' profitability and their effect on their overall performance. Different bank-specific, industry-specific, and macroeconomic determinants were identified and assumed based on a revision of the existing literature in Chapter 3. The choice of variables employed in the current research considers the characteristics of the UK banking sector, including recent events such as Covid-19 (COV) and the changes in financial regulations from 2010- 2021.

The change in regulations was significant, both domestically and internationally. The international structure moved from the initial Basel I agreement, which focused on establishing capital requirements for credit risk, to Basel II, authorising more widespread use of internal models for setting capital requirements. Domestically, regulations were developed in forms unique to the UK, with bank-specific supervisory add-ons to capital and liquidity requirements that can help overcome classification challenges for causal inference (De-Ramon, Francis and Milonas 2017). Also, following the financial crisis of 2007/09, the Bank of England had its regulatory powers reinstated. In addition to regulatory responsibility shifting back to the Bank of England, three new bodies were set up: The Financial Policy Committee (FPC), the Prudent Regulatory Authority (PRA), and the Financial Conduct Authority (FCA). The new structure came into operation on the 1st of April 2013. For more details, see Chapter 2, Section 2.5.

This chapter focuses on empirical data analysis. Thirty econometric models (one model of OLS and FE and four GMM models for each proxy of profitability) were used to investigate the association between the UK banks' profitability (Return on assets, return on average assets, return on equity, return on average equity, and net interest margin as proxied by ROA, ROAA, ROE, ROAE, and NIM, respectively) and the presumed internal and external explanatory variables. The investigation is based on an unbalanced panel dataset covering 416 bank-year observations of 38 domestic and foreign commercial banks operating in the UK banking sector from 2010 to 2021. Also, this research provides an empirical result of investigating the determinants of bank profitability before and after Brexit by analysing the sub-samples (pre and post-Brexit).

The chapter illustrates the econometric results, including the descriptive statistics, the test for multicollinearity, and regression analysis using the OLS, FE, and GMM models. The chapter is organised as follows. Section 5.2 presents the descriptive statistics for the variables used in the regression analysis. Section 5.3 presents the correlation matrix and the test for multicollinearity. Section 5.4 presents the models and steps used in the estimation process. Section 5.5 shows the results of the regression analysis for the whole sample. Section 5.6 presents 5.6 the results of investigating the determinants of bank profitability before and after Brexit. A summary of the findings is provided in Section 5.7.

5.2 Descriptive statistics

Table 5.1 presents the summary statistics of the dependent and independent variables used in the empirical models. The scores' ROE and ROAE values have significant dispersion, as demonstrated by the minimum, maximum, and standard deviation values. On average, UK commercial banks included in the sample show ROE and ROAE of 3.38% and 3.87%, respectively, over the whole period from 2010 to 2021. ROE values range from -42.94% to 24.14%, while ROAE ranges from -41.51% to 35.31%. These two measures have the highest standard deviation between the profitability measures of 10.79% for ROE and 11.48% for ROAE. The mean and standard deviation difference indicates significant differences in the UK banks' profitability. The wide ranges between these values reflect the fluctuations in banks' profit during this period and the sizes of banks used in the research sample.

Table 5.1: Summary statistics for all variables employed in the empirical models.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Dependent variables					
ROA	416	0.36	1.06	-4.42	3.03
ROAA	416	0.38	1.16	-4.68	3.39
ROE	416	3.38	10.79	-42.94	24.14
ROAE	416	3.87	11.48	-41.51	35.31
NIM	416	2.27	1.71	0.001	9.21
Independent variables					
SIZE	416	23.03	2.32	19.18	28.28
NPL	416	8.85	28.39	0.006	201.99
FGR	416	-0.06	0.22	-0.72	0.35
LCR	416	234.07	145.03	102	823
NSFR	416	186.53	115.91	81.6	658.40
ETR	416	0.29	0.72	-0.92	5.45
LOANGR	416	0.15	0.47	-0.40	2.97
LOAN	416	48.70	24.14	1.60	91.89
DEP	416	0.55	0.25	0.00	0.93
OE	416	73.95	39.80	25.15	300.28
MC	416	48.70	5.98	38.76	57.65
PC	416	0.72	0.44	0	1
DB	416	0.54	0.50	0	1
INF	416	2.92	1.17	1	5.2
GDPGR	416	1.22	3.79	-9.8	6.7
COV	416	0.18	0.38	0	1

Note: ROA; Return on assets, ROAA; Return on average assets, ROE; Return on equity, ROAE; Return on average equity, NIM; Net interest margin, SIZE; Bank size, NPL; Non-performing loan ratio, FGR; Financing gap ratio, LCR; Liquidity coverage ratio, NSFR; Net stable funding ratio, ETR; Effective tax rate, CAR; Capital adequacy ratio, LOANGR; Laon growth ratio, LOAN; Loan specialization ratio, DEP; Deposits ratio, AQ; Asset quality, OE; Operating efficiency, MC; Market concentration, PC; Ownership structure: Dummy variable equals1 for publicly quoted banks, and 0 otherwise, DB; Ownership status: Dummy variable equals1 for domestic banks, and 0 otherwise, INF; Inflation rate, GDPGR; GDP growth rate, COV; Covid-19: Dummy variable equals 1 for the years of (Covid-19) 2020-2021 and 0 otherwise.

The banks in this research sample show an average ROA and ROAA of 0.36% and 0.38% and a relative standard deviation of 1.06% and 1.16%, respectively. The values of ROA range between -4.42% and

3.03%, while -4.68% to 3.39% for ROAA. The fifth profitability measure, NIM, averages 2.27% on average, with a standard deviation of 1.71%. The banks' NIM value ranges between 0.001% and 9.21%. On the contrary, the independent variables show variations evident by their minimum and maximum values, especially the bank-specific variables. There is a significant variation in the SIZE, NPL, LCR, NSFR, LOAN and OE data set. This variation is due to using a sample that includes different banks in sizes, deposits, capital, and loans.

It can be said that the notable difference among banks in this research sample regards their sizes (measured by total assets). Some banks, such as HSBC Holding Plc, Barclays Plc, Lloyds Banking Group Plc, and NatWest Group Plc, have a large size in terms of total assets, and they use higher capital as they are established for an extended period. Other banks have small sizes and thus minor capital and equity, which downturn banks' ROA, ROAA, ROE, and ROAE.

As can be seen from Table 5.1, the most significant values of the mean and standard deviation among the independent variables are for LCR, NSFR, and OE. The mean values are 234.07%, 168.53%, and 73.95%, while the standard deviation values are 145.03%, 115.91%, and 39.80%, respectively. The other independent variables, internal variables such as FGR, ETR, LOANGR, and DEP, and external variables such as GDPGR, INF, COV, DB, and PC, have lower standard deviation values, indicating more consistency in the data set. The MC ratio averages 48.70%, which ranges between 38.76% and 57.65% for the sample. The value of this ratio is expected as it is calculated as the sum of the market share of the big four banks working in the sector, as the "Big Four" concept exists in the UK banking sector. The maximum value of 57.65% for MC stands for the year 2021, which indicates that the market is oligopolistic.

The efficiency level is based on banks' ability to reduce operating expenses or increase revenues. As the ratio is calculated by dividing the operating expenses by the operating revenues, banks with lower values work more efficiently than others with high values. The best-efficient bank in the research sample has an OE of 25.15, whereas the least-efficient bank's ratio of OE amounts to 300.28.

5.3 Correlation matrix and multicollinearity test

Before running the regression analysis, the independence of variables to be free from multicollinearity problems that may prejudice the results was checked using the correlation matrix. The results in Table 5.2 demonstrate that collinearity problems do not exist between independent variables.

Table 5.2: The correlation matrix for the variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
1) ROA	1																				
2) ROAA	0.98***	1																			
3) ROE	0.88***	0.85***	1																		
4) ROAE	0.89**	0.88**	0.98**	1																	
5)NIM	0.51	0.53**	0.45**	0.47	1																
6) SIZE	-0.09	-0.09	-0.06*	-0.07	-0.17	1															
7) NPL	-0.14***	-0.16	-0.10*	-0.09**	-0.19***	-0.11	1														
8) LOANGR	-0.07**	-0.08**	-0.01**	-0.02	0.16**	-0.24**	-0.07	1													
9) FGR	0.16**	0.15***	0.10**	0.09*	0.21***	0.14	-0.38**	-0.05	1												
10) LCR	0.26*	0.24	0.21*	0.21	0.51	-0.36**	-0.02	0.12	0.16	1											
11) NSFR	0.27**	0.24	0.21	.21*	0.51	-0.35	-0.02	0.12	0.17	0.48	1										
12) ETR	-0.03	-0.02	-0.01**	-0.02	-0.01	0.04**	0.01**	-0.05*	-0.01*	-0.07	-0.06	1									
13) LOAN	-0.16	-0.18	-0.08	-0.11***	-0.16	-0.20	0.48	0.01	-0.25	-0.04	-0.04	-0.01	1								
14) DEP	0.13*	0.14*	0.14	0.16**	0.39	-0.18	-0.00***	0.17	-0.49	0.05***	-0.01	-0.04	0.47**	1							
15) OE	-0.42	-0.42	-0.41	-0.42	-0.22	0.01	0.15	0.22*	-0.21	-0.08*	-0.01	0.21*	-0.15**	0.04	1						
16) MC	-0.08	-0.09	-0.06**	-0.07	-0.09	-0.03	0.07	0.07	-0.05	-0.09	-0.09	-0.05	-0.00	0.13	0.10	1					
17) PC	0.01	0.00	-0.04	-0.03	-0.24	-0.46**	0.11	-0.00	-0.11	-0.02	-0.02	0.00	-0.23	0.19	0.01	-0.43	1				
18) DB	0.02**	0.03	0.10	0.10**	0.39	0.26	-0.15	0.17	-0.08	0.10*	0.09	-0.08**	0.44	-0.23	0.19	0.01	-0.43	1			
19) INF	-0.05	-0.04	-0.00*	-0.00*	-0.07	0.03	0.01	-0.05**	0.04	-0.06	-0.06	0.04	-0.08**	0.13	-0.06	-0.09	-0.03	-0.00	1		
20) GDPGR	0.02	0.02**	0.03	0.03	-0.02***	-0.02	0.03	0.04	-0.01	-0.03**	-0.03	0.02**	-0.00	-0.01	0.00	-0.03	-0.00	0.00	0.41	1	
21) COV	0.04**	0.04	0.07***	0.06	0.02	0.04*	-0.03	-0.11**	-0.01	0.04*	0.04	-0.09	0.02	-0.00	-0.04	0.26	0.01	0.01	-0.04	-0.32	1

Note: The *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively.

Regression analysis aims to isolate the relationship between independent and dependent variables. The performance of a regression coefficient is that it describes the mean change in the dependent variable for each 1-unit change in an independent variable when holding all the other independent variables constant. Multicollinearity can happen when independent variables in a regression model are correlated. This correlation is a problem because independent variables should be independent. If the correlation between variables is high enough, it can cause problems fitting the model and interpreting the results. These problems are that the coefficient estimates can swing wildly based on other independent variables. The coefficients become sensitive to slight changes in the model. Also, multicollinearity lowers the estimated coefficients' precision, weakening the regression model's statistical power. This might lead to unreliable p-values to identify statistically significant independent variables.

Following Nguyen and Stewart (2020) and Hamid (2017), a decision was made to remove one variable from each pairwise with a correlation coefficient higher than 0.50. This procedure is to overcome the multicollinearity issue and make the models used in this research valid and dependable. As shown in Table 5.2, most pairwise combinations of variables have a simple correlation coefficient below 0.5, as research uses panel data with sample sizes of 416 observations, which should be large enough to reduce the detrimental effects of multicollinearity.

Table 5.2 shows that the ROA, ROAA, ROE, and ROAE are highly correlated as they are popular competitors for measuring profitability. This correlation is expected and not considered a problem as these dependent variables are run into different models and analysed separately. The table also presents the levels of significance between variables.

5.4 Models and steps used in the estimation process

5.4.1 Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators

The standard estimators applied to dynamic panel data models, which need to account for cross-sectional fixed effects, indicate the following properties. Firstly, the dynamic models can be consistently estimated when T is large, so dynamic panel bias should not be an issue. Second, the OLS estimator shows dynamic panel bias and is inconsistent when the number of time-series observations (T) is small, even if the number of cross-sectional units (N) is large. Lastly, the coefficient of the lagged dependent variable is upward biased when applying the OLS to a dynamic panel model when T is small. The FE estimator is also biased and inconsistent, as N increases, for small T when using dynamic panel models. The bias and inconsistency of the FE estimator vanish as T increases. Regardless, this estimator can still have a substantial bias (20%) when T = 30 (Roodman 2009).

The coefficient of the lagged dependent variable is downward biased when the FE estimator is used when estimating dynamic panel models with a small T. As these two estimators, OLS and FE, are biased in opposite directions for the coefficient of the lagged dependent variable, both estimators are applied to show a range that the lagged dependent variable's population coefficient is expected to be within. As these two estimators have a sampling distribution that could offset the bias of one or both estimators, the population coefficient may not fall in this range (Roodman 2009).

5.4.2 The Generalized Method of Moments (GMM) estimator

The GMM estimators are designed for panels with small T and large N. This research applies the difference and system GMM dynamic panel estimators, which are consistent as N (though not T) tends to infinity. As the latter is expected to be more suitable for modelling (stationary) near unit root processes than the former (Roodman 2009), considering both supports ensure appropriate modelling of this research's data regardless of the data generation process.

For both difference and system GMM methods, the current research applies the one-step estimator (with coefficient standard errors that are robust to autocorrelation and heteroscedasticity) and the two-step estimator (with Windmeijer, 2005, small sample corrected robust coefficient standard errors).

While the two-step coefficient estimator is asymptotically efficient and superior to the one-step estimator, the two-step coefficient standard errors are biased downwards, although the Windmeijer (2005) correction dramatically reduces this problem (Roodman 2009). Given that one form of GMM estimator is not unambiguously outstanding from the others, the research considers all four to evaluate their relative performance.

All regressors except for the lagged dependent variable are assumed to be strictly exogenous because industry-specific or macroeconomic covariates are unlikely to be significantly influenced by individual banks or lagged by one period. All assumed exogenous variables included in a model are used as IV-style instruments. This research appropriately uses the lagged dependent variable as the basis for the GMM-style instruments. As the number of GMM-style instruments equals the number of time-series observations (T), the GMM-style instruments collapsed into one is used to avoid having so many instruments that the instrument equation is overfitted and does not remove the endogeneity of the lagged dependent variable. Roodman (2009) states that using collapsed GMM-style instruments generates a slight loss of estimation efficiency. Regardless, in some instances, the GMM-style instruments will not be collapsed into one to ensure the equations are over-identified.

Hansen's J-statistic tests the instruments' exogeneity, allowing for heteroscedastic and autocorrelated residuals. However, as the number of instruments increases, the test's power falls such that it becomes biased towards accepting the null of exogenous instruments. To avoid overly reducing the power of this test and to ensure the instrumented equation is not overfitted, it is essential not to use too many instruments. Roodman (2009) suggests that there are too many instruments if there are more instruments than cross-sectional units in the panel. It is ensured that the number of instruments is lower than the number of cross-sections for all models estimated by GMM. Also, for models estimated by GMM to be valid, the following conditions must be met: no second-order autocorrelation and no instrument invalidity. For comparison purposes, the following section reports the results of the profitability models, ROA, ROAA, ROE, ROAE, and NIM, estimated by OLS, FE, and GMM estimators.

5.5 Results of the regression analysis of the entire sample

Before presenting the analysis results in detail, it is crucial to give an overview of the main concepts and abbreviations in Table 5.5, Table 5.6, and Table 5.7. The following Section, 5.5.1, outlines the meanings of these concepts and the abbreviations with their values.

5.5.1 An outline of the main results for all profitability models using all estimators

All the estimators discussed above (OLS, FE, and GMM) are used to estimate the profitability models for the UK banking sector. Four versions of the GMM estimator are used, employing the (system) and (difference) estimators with both (one-step) and (two-step) procedures. Due to endogeneity bias (Ullah, Akhtar and Zaefarian, 2018), the results of the analyses indicate significant differences in findings reported under the OLS, FE, and GMM estimators.

In all the following Tables (Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7), 1D and 2D indicate the one and two-step difference estimators, and 1S and 2S imply the one and two-step system estimators. Also, the number of observations is noted in the row labelled Obs. The rows labelled 'groups' and 'instruments' give the number of cross-sectional units and instruments, respectively. For all models estimated by GMM, the number of instruments is below the number of cross-sectional units to avoid the problems associated with using too many instruments. AR (1) and AR (2) present the Arellano and Bond tests for first and second-order autocorrelation, while (Hansen) presents Hansen's test for instrument validity.

The null hypothesis of the Hansen test is that the instruments as a group are exogenous. The Arellano and Bond test's null hypothesis is that there is no autocorrelation, and it is applied to the differenced residuals.

The AR (2) test in first differences is essential as it detects autocorrelation in levels. A model is considered valid when p-values for all these tests exceed 0.05.

As shown in Table 5.3, Table 5.4, Table 5.5 and Table 5.6, the ROA, ROAA, ROE and ROAE models, estimated by the four versions of the GMM estimator (system and difference estimators with both one-step and two-step procedures), exhibit evident second-order autocorrelation or instruments validity as the p-values of AR (2) and (Hansen) are equal to or exceed 0.05, which indicates that they are valid for inference. Another point that the estimators are valid for inference is that the number of groups is higher than the number of instruments for all estimators.

Given the discussion above, it can be concluded that estimations in the current research are robust and consistent. As can be observed in the tables, insignificant AR (2) tests indicate that error terms do not have second-order autocorrelation. Also, the insignificant Hansen test of over-identifying restrictions (with high p-values) signifies that the models used are accurately specified, assuming there is no evidence of a correlation between instruments and errors.

Tables (Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7) report the profitability models estimated over the entire sample, including all determinants with ROA, ROAA, ROE, ROAE, and NIM as the dependent variables. The lagged dependent variable ROA_{t-1} is significant at level 0.01 for the OLS estimator, while it is significant at level 0.05 for the FE and all GMM estimators, except for the GMM one-step difference, where it is significant at level 0.10; see Table 5.3. The lagged dependent variables $ROAA_{t-1}$ and $ROAE_{t-1}$ are significant at level 0.01 for all estimators except the GMM two-step system estimator, which is significant at level 0.05; see Table 5.4 and Table 5.6. The ROE_{t-1}, as presented in Table 5.5, is significant at level 0.01 for the OLS estimators, while it is significant at 0.05 for all other estimators. The lagged dependent variable NIM_{t-1} is significant at level 0.01 for all estimators; see

Table 5.7. These results strongly reinforce the inclusion of these lagged variables in the models and suggest that the OLS and FE estimators will be subject to dynamic panel bias and should not be used for inference. Also, the coefficients on the lagged dependent variables $ROA_{t-1,}$ $ROAA_{t-1}$, ROE_{t-1}, $ROAE_{t-1,}$ and NIM_{t-1} are between 0 and 1 for all estimators, implying that bank profitability persists over time for all those with coefficients between 0 and 1.

As the present research focuses on the GMM estimators' results for the entire sample analysis, the preference of the appropriate model to be discussed is based on the value of the standard deviation (Std. Err) of the lagged dependent variable; the estimator with the lowest standard error is the preferred one. This method is applied to all GMM estimators for all profitability measures. Under this method, the GMM estimator 2D is preferred for ROA and ROAA models, while the 2S estimator is for ROE, ROAE, and NIM models.

5.5.2 OLS, FE, and GMM results for all profitability models of the whole sample

Tables (Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7) display the full sample results of regressions between the independent variables and the banks' profitability, measured by ROA, ROAA, ROE, ROAE, and NIM.

For all profitability models, ROA, ROAA, ROE, ROAE and NIM, with all GMM estimators, the bank-specific variables LCR, NSFR, ETR, LOAN and the industry-specific and macroeconomics variables MC, PC, INF, GDPGR (except for ROA and ROAA), COV (except for NIM) do not appear to be determinants for UK banks profitability as the coefficients for all mentioned variables are insignificant. However, the focus in this section will be on the general interpretation of significant essential variables to ease the exposition of the results, the results of the preferred GMM estimator. For significant results of other estimators, OLS and FE, see Tables (Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7).

All regression models show that the lagged dependent variables ROA_{t-1}, $ROAA_{t-1}$, ROE_{t-1}, $ROAE_{t-1,}$ and NIM_{t-1} are positive and significant. As mentioned in the previous section, this strongly supports their inclusion in the models and suggests that the OLS and FE estimators will be subject to dynamic panel bias and should not be the only estimators used for inference.

The highly significant coefficient of the lagged dependent variables proves the dynamic character of the model's specification. In the current research, the coefficients of ROA_{t-1} and $ROAA_{t-1}$, ROE_{t-1}, $ROAE_{t-1,}$ and NIM_{t-1} take values between 0.1409 and 0.9528 for the GMM estimators, which means that profits appear to persist to a moderate extent, and indicates that departures from a perfectly competitive market structure in the UK banking sector may not be that large (Athannasoglou, Brissimis and Delis 2008; Dietrich and Wanzenried 2014; Djalilov and Piesse 2016). Regardless, Goddard and Wilson (2009) found weak statistical evidence for profit persistence in European banks.

For bank-specific variables, there was no prior expectation of the impact of SIZE on UK bank profitability, as the literature review supports both positive and negative impacts. According to the economies of scale theory (Goddard, Molyneux and Wilson 2004), larger banks are anticipated to be more profitable since they spread costs throughout their systems, resulting in a lower operation cost. Furthermore, the significant credits would ease banks’ spreads and reduce lending rates, enhancing competitive ability with other financial institutions in providing credit products (Trad, Trabelsi and Goux 2017).

Contrary to the two arguments and the results of authors (Short 1979; Smirlock 1985; Bikker and Hu 2002; Pasiouras and Kosmidou 2007; Guillén, Rengifo and Ozsoz 2014), who find that SIZE has a positive impact on bank performance, this research finds an adverse effect of SIZE on bank's profitability. Based on the preferred GMM estimator for each model, mentioned in Section 5.5.1, the results presented in Tables (Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7) show that SIZE, as a bank-specific variable, is negatively correlated with ROA, ROAA, ROE, ROAE and NIM. The coefficients on SIZE are significantly different from zero at the 10% level for all profitability models. These results are in line with previous studies that applied the GMM models (Kosmidou, Tanna and Pasiouras 2008; Dietrich and Wanzenried 2011; Le, Nasir and Huynh 2020), who found a negative association between bank size and the stated profitability measures.

The results are supported by the evidence that the larger the bank is, the harder it will be to manage (Cerasi and Daltung, 2000). Also, larger banks may take more risks due to governments' bailout, commonly called the "too-big-to-fail" policy. The idea behind this is that policymakers will be inclined to bail out institutions considered to be of "systemic" importance, that is, institutions whose potential failure could threaten the stability of the entire financial system (Dávila and Walther 2020).

In the context of the UK, the results of this research are consistent with the findings of Kosmidou et al. (2006), who compare the performance of UK banks over the period 1998- 2002, and Kosmidou, Tanna and Pasiouras (2008), who investigated the impact of bank-specific characteristics, macroeconomic conditions and financial market structure on the UK owned commercial banks' profits, during the period 1995-2002. Their findings were that smaller banks are more profitable and perform better than larger banks.

The previously mentioned studies that find a positive impact of SIZE argue that significant size decreases costs due to the economies of scale, as banks of significant size can raise capital at a lower cost. Regardless, scale economies are not the only way size can affect profitability. Berger et al. (2005) argue that small banks may form stronger connections with local businesses and customers than large banks, allowing them access to proprietary information to set contract terms and make better credit underwriting decisions. Indeed, these informational and pricing advantages may fully offset any loss of scale economies. The research results show that increasing the bank's size could increase operational costs. Although banks are reducing their branch network and the number of employees, there is still a minimum limit they cannot go under if they want to maintain the same level of service they already provide to their customers, which leads to fixed costs that could be hard to reduce. It can be inferred that an increase in size does not necessarily cause an increase in net returns. However, banks with higher returns could be sufficiently positioned to grow.

The coefficients of NPL show the expected negative sign. In line with previous findings of Ciukaj and Kil (2020) and Ozili (2019), the results shown under the 2D estimator for ROA and ROAA and 2S for NIM exhibit that NPL is negatively associated with bank profitability. The coefficients on NPL are statistically significant at the 0.10 level for these three profitability measures. The NPL ratio threatens commercial banks' financial stability and the national monetary security system. Commercial banks will lose much capital when bad debts exceed the permitted limit. This affects cash flows, and banks will become illiquid, leading to possible bankruptcy and risk to banks' sustainable development and profitability.

Bad debt reduces profits due to risks that lead to many financial losses. Credit is the fundamental activity of the bank, bringing in the primary revenue source. However, the revenue from credit activities entailed credit risks. The unrecovered debt causes commercial banks' capital to diminish, leading to difficulty in making a profit. Studies from Andries (2011), Banker, Chang and Lee (2010), Athanasoglou et al. (2008) and Demirgüç-Kunt and Huizinga (1999) found an adverse correlation between the bad debt ratio and the profitability of commercial banks. They conclude that when the NPL ratio increases, the bank's profitability will be decreased. The current research results recommend that instead of focusing on lending, UK commercial banks should focus more on screening and monitoring the loan default risk to maximize their profit-making ability.

Since loans are a primary source of banks' interest income, it is found that LOANGR has a significant positive statistical effect on UK banks' NIM presented under the preferred GMM model 2S in Table 5.7. The results on LOANGR meet the expected sign, with a coefficient being highly statistically significant at the 0.01 level. The result is in line with Le (2020), Dang (2019), and Al-Khouri and Arouri (2016), indicating that profitable banks are more likely to raise credit since they can attract more funds. Also, the bank's lending expansion generally causes better profitability. The current research recommends that UK commercial banks keep the growth rate in loans at the optimal level, as excessive loan growth may lead to more significant risks through increasing the NPL, which could be translated to a decrease in bank profitability.

Regarding OE, the cost-to-income ratio, the variable's coefficients exhibit the expected negative sign using all estimators. Concerning the significant values, the results under the 2D estimator in Table 5.3 and Table 5.4 and under the 2S estimator in Table 5.5 and Table 5.6 show that OE has a negative impact on UK commercial banks’ profitability: ROA, ROAA, ROE, and ROAE. The coefficients on OE are highly statistically significant at a 0.01 level for all mentioned profitability measures. Banks use this OE for tracking the movements of their costs versus their income for the same period. A high cost-to-income ratio may indicate that a bank is not efficiently managed or that a high competition level exists in the banking industry. As the calculations of this ratio depend on cost and income figures, banks could lower the ratio's value by either increasing their operating revenues or decreasing their operating expenses. The significant negative results meet this research's expectations and align with the results of (Athanasoglou, Brissimis and Delis 2008; Dietrich and Wanzenried 2011).

Considering the impact of the deposit ratio on profitability, this research finds that DEP positively affects profitability, with coefficients being significant for ROA and NIM models. The impact of DEP on ROA and NIM for the UK commercial banks is small, at the 10% significance level for both models. The positive results found in this research meet the expected positive sign and confirm the findings of Saeed (2014) and Lee and Hsieh (2013), indicating that increasing customer deposits leads to a growth in the funds available for different profitable opportunities such as lending and investments; consequently, increasing banks' profitability. However, if banks cannot release money through loans, their profitability level decreases due to paying interest to depositors on their fixed, time, or term deposits. It could be recommended that UK commercial banks hold optimal deposits, which can be transferred into high-quality loans, hence gaining profits.

The macroeconomic variable COV is found to impact NIM significantly. The result on COV meets the expected negative sign. As presented in Table 5.7, the impact of COV on NIM for the UK commercial banks is small, at the 10% significance level. This weak negative correlation indicates the ability of the UK government and the Bank of England to provide a plan that could weaken the significant impact of the pandemic on the UK economy in general. The response of the Bank of England to the pandemic was clear and compelling. The BoE was performed to save jobs and support the UK economy through measures and determinations. According to the Bank of England (2020a), in March 2020, the BoE cut its interest rate (Bank Rate). The cut in the Bank Rate offered the UK banks and building societies long-term funding at interest rates of 0.1%. This results in cheaper loans for businesses and households. That reduced the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households.

Table 5.3: The full sample profitability model including all variables with ROA as the dependent variable using all estimators.

Variables	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
	(1)	(2)	(3)	(4)	(5)	(6)
ROA_{t-1}	0.3202*** (7.44)	0.0970** (1.97)	0.2109** (1.53)	0.2084** (2.19)	0.2001** (1.45)	0.1891* (1.70)
			{0.137}	{0. 095}	{0.138}	{0.111}
SIZE $_{t-1}$	-0.0422* (-1.48)	-0.0932 (-0.94)	-0.0433* (-0.69)	0.0235* (0.13)	-0.0478* (-0.86)	0.0159* (0.13)
NPL_{t-1}	0.0001 (0.08)	-0.0091** (-2.52)	-0.0035 (-0.93)	-0.0171* (-1.07)	-0.0031 (-0.93)	-0.0218** (-2.22)
$LOANGR_{t-1}$	0.0320 (0.36)	-0.1974 (-1.84)	-0.0694 (-0.60)	-0.0837 (-0.76)	-0.0403 (-0.39)	-0.0601 (-0.58)
FGR $_{t-1}$	0.9007*** (2.63)	0.4687 (2.28)	0.060 (0.96)	0.3052 (1.81)	0.2506** (2.03)	0.9345*** (2.77)
LCR_{t-1}	-0.0025 (-0.42)	0.0000 (0.01)	-0.0014 (-0.51)	0.0025 (0.62)	-0.0016 (-0.62)	0.0012 (0.27)
$NSFR_{t-1}$	0.0039 (0.54)	0.0002 (0.01)	0.0027 (0.76)	-0.0025 (-0.43)	0.0030 (0.93)	-0.0004 (-0.07)
ETR $_{t-1}$	0.0036 (0.09)	0.0004 (0.01)	-0.0132 (-0.64)	0.0027 0.08)	-0.0100 (-0.57)	0.0197 (0.71)
LOAN $_{t-1}$	-0.1349** (-2.56)	-0.1055* (-1.95)	-0.1578 (-0.95)	-0.0967 (-1.63)	-0.1571** (-1.97)	-0.1052** (-2.25)
DEP $_{t-1}$	0.7181*** (2.61)	0.9265** (2.19)	0.0625 (0.97)	0.3127* (1.78)	0.0221** (2.00)	0.9715** (2.46)
OE $_{t-1}$	-0.0110*** (-10.37)	-0.01094*** (-8.23)	-0.0117*** (-4.20)	-0.01169*** (-2.92)	-0.01256*** (-4.91)	-0.0115*** (-5.05)
MC	0.0045 (0.76)	0.0017 (0.28)	0.0084 (1.59)	0.0097 (1.10)	0.0100 (1.57)	0.0140 (1.43)
PC	-0.0809 (-0.68)		-0.1050 (-0.43)		-0.0916 (-0.41)	
DB	0.1846* (1.87)	-0.3931 (-0.63)	0.1520 (1.06)	0.1091 (0.40)	0.1983 (1.58)	-0.0461 (-0.17)
INF	-0.0493 (-1.43)	-0.05932* (-1.79)	0.0036 (0.08)	0.0234 (0.51)	-0.0346 (-0.61)	-0.0055 (-0.10)
GDPGR	0.0239** (2.46)	0.0260*** (2.83)	0.0137 (1.43)	0.0137 (1.31)	0.0200* (1.82)	0.0207* (1.68)
COV	0.0340 (0.37)	0.0691 (0.71)	-0.0477 (-0.46)	-0.0879 (-0.44)	-0.0464 (0.50)	-0.1408 (-0.70)
Constant	1.5977* (1.74)	2.9785 (1.19)	1.3114 (0.64)		1.4628 (0.78)	
Obs.	378	378	378	340	378	340
Groups	38	38	38	38	38	38
Instruments			36	27	36	27
AR (1) (p-value)			0.073*	0.040**	0.036**	0.006***
AR (2) (p-value)			0.773	0.818	0.830	0.856
Hansen			0.296	0.133	0.296	0.133

Note: Coefficients and t-statistics (round brackets) are reported. Standard deviations of lagged dependant variables for GMM estimators {curly brackets} are presented. *, ** and *** donate significance at the 10%, 5% and 1% level, respectively. Obs. indicates the total number of observations, while groups represent the number of cross-sectional units. Instruments are the number of instruments. AR (1) and AR (2) denote tests for first and second-order autocorrelation, respectively, while Hansen gives Hansen's J-statistic for instrument validity. OLS denotes the Ordinary Least Square estimator; FE the Fixed Effect estimator; GMM denotes the Generalised Method of Moments estimator; 2S the two-step system estimator; 2D the two-step difference estimator; 1S the one-step system estimator; 1D the one-step difference estimator. GMM 2D and 1D models use the GMM method without collapsing the GMM-style instruments to ensure the models are over-identified. Sources: Annual financial statements of 38 UK commercial banks from 2010 to 2021.

Table 5.4: The full sample profitability model including all variables with ROAA as the dependent variable using all estimators.

Variables	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
	(1)	(2)	(3)	(4)	(5)	(6)
$ROAA_{t-1}$	0.3613^{***} (8.87)	0.1462^{***} (3.06)	0.2663^{**} (2.25)	0.2936^{***} (3.25)	0.2916^{***} (2.86)	0.2572^{***} (2.70)
			{0. 118}	{0.090}	{0.101}	{0.095}
$SIZE_{t-1}$	-0.0336^{**} (-1.12)	-0.0947 (-0.91)	-0.1582^{*} (-0.94)	-0.0153^{*} (0.08)	-0.0336^{*} (-0.63)	-0.0431^{*} (0.35)
NPL_{t-1}	-0.0005 (-0.26)	-0.0114^{***} (-3.00)	-0.0044 (-1.34)	-0.0185^{*} (-1.82)	-0.0047 (-1.39)	-0.0260^{**} (-2.52)
$LOANGR_{t-1}$	0.0601 (0.64)	-0.2383^{**} (-2.08)	-0.0662 (-0.46)	-0.0927 (-0.84)	-0.0003 (-0.00)	-0.0922 (-1.02)
FGR_{t-1}	4.2433^{**} (2.57)	1.6339^{**} (2.03)	5.5573 (1.22)	9.8628 (1.10)	5.7435^{*} (1.84)	2.4558^{**} (2.16)
LCR_{t-1}	-0.0030 (-0.49)	-0.0001 (-0.01)	-0.0031 (-1.14)	0.0033 (0.80)	-0.0027 (-0.99)	0.0010 (0.22)
$NSFR_{t-1}$	0.0047 (0.62)	0.0008 (0.05)	0.0040 (1.25)	-0.0031 (-0.50)	0.0044 (1.33)	0.0001 (0.02)
ETR_{t-1}	0.0087 (0.19)	-0.0006 (-0.02)	-0.0088 (-0.43)	-0.0063 (-0.18)	-0.0105 (-0.58)	0.0174 (0.58)
$LOAN_{t-1}$	-0.1379^{**} (-2.50)	-0.0975^{*} (-1.72)	-0.1530 (-1.20)	-0.0765 (-0.95)	-0.1522^{*} (-1.78)	-0.0915^{*} (-1.71)
DEP_{t-1}	4.0385^{**} (2.55)	0.8818^{*} (1.91)	5.2841 (1.21)	8.8162 (1.03)	5.5280^{*} (1.82)	0.1835^{*} (1.83)
OE_{t-1}	-0.0110^{***} (0.11)	-0.0108^{***} (-7.83)	-0.0122^{***} (-2.93)	-0.0125^{***} (-2.84)	-0.0121^{***} (-4.94)	-0.0118^{***} (-4.97)
MC	0.0035 (0.57)	0.0022 (0.35)	-0.0005 (-0.05)	0.0108 (1.09)	0.0098 (1.38)	0.0144 (1.37)
PC	-0.0209 (-0.17)		-0.4715 (-0.77)		-0.0112 (-0.05)	
DB	0.2215^{**} (2.14)	-0.4318 (-0.66)	0.2894 (1.46)	0.1031 (0.37)	0.2357^{**} (1.89)	-0.1232 (1.83)
INF	-0.0546 (-1.52)	-0.0611^{*} (-1.76)	-0.0245 (-0.41)	0.0302 (0.55)	-0.0355 (-0.62)	-0.0164 (-0.27)
GDPGR	0.0242^{**} (2.38)	0.0266^{**} (2.76)	0.0135 (1.50)	0.0102 (0.76)	0.0198^{*} (1.75)	0.0230^{*} (1.78)
COV	0.0134 (0.14)	0.0234 (0.23)	0.0011 (0.01)	-0.1141 (-0.49)	-0.0618 (-0.62)	-0.1568 (-0.74)
Constant	1.3201 (1.37)	3.0814 (1.17)	4.9987 (0.89)		0.9385 (0.52)	
Obs.	378	378	378	340	378	340
Groups	38	38	38	38	38	38
Instruments			36	27	36	27
AR (1) (p-value)			0.056^{*}	0.032^{**}	0.020^{**}	0.002^{***}
AR (2) (p-value)			0.673	0.786	0.744	0.810
Hansen			0.494	0.064	0.494	0.064

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

Table 5.5: The full sample profitability model including all variables with ROE as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
ROE_{t-1}	0.2430*** (5.42)	0.0659 (1.35)	0.1967** (2.48)	0.1859 (1.49)	0.2009** (2.15)	0.1409 (1.40)
			{0. 079}	{0. 124}	{0.093}	{0.100}
$SIZE_{t-1}$	-0.5188 (-1.64)	-0.7603*** (-3.39)	-0.1663* (-0.39)	-0.2084* (-1.19)	-0.4005* (-0.92)	-0.0337* (-1.24)
NPL_{t-1}	0.0076 (0.36)	-0.1719*** (-4.21)	-0.0246 (-0.92)	-0.2392 (-1.13)	-0.0403 (-1.04)	-0.2726** (-2.31)
$LOANGR_{t-1}$	0.9285 (1.03)	-1.8068 (-1.58)	0.862 (0.77)	-0.8043 (-0.40)	0.8167 (0.79)	-0.8820 (0.66)
FGR_{t-1}	3.9001* (1.93)	7.0680 (0.61)	3.7339 (1.04)	6.0651 (1.09)	9.8417 (1.63)	3.8820** (1.96)
LCR_{t-1}	-0.0090 (-0.14)	0.0529 (0.38)	0.0127 (0.36)	0.0579 (0.92)	-0.0067 (-0.26)	0.0256 (0.46)
$NSFR_{t-1}$	0.0156 (0.19)	-0.0649 (-0.36)	-0.0097 (-0.22)	-0.0631 (-0.73)	0.0151 (0.46)	-0.0153 (-0.20)
ETR_{t-1}	0.3604 (0.75)	0.2857 (0.61)	0.0188 (0.06)	0.2457 (0.37)	0.2112 (0.85)	0.5906 (1.41)
$LOAN_{t-1}$	-1.1416* (-1.94)	-0.2468 (-0.41)	-1.3499 (-1.04)	-0.5114 (-0.77)	-1.2992 (-1.61)	-0.6498 (-1.43)
DEP_{t-1}	3.872* (1.94)	6.3626 (0.60)	5.7719 (1.05)	1.1676 (1.02)	3.4178 (1.63)	5.5867* (1.80)
OE_{t-1}	-0.1472*** (-11.98)	-0.1445*** (-9.63)	-0.1614*** (-5.34)	-0.1538*** (-2.98)	-.15669*** (-5.52)	-0.1499*** (-3.85)
MC	0.0392 (0.59)	-0.0330 (-0.48)	0.0610 (1.05)	0.0394 (0.41)	0.10658 (1.46)	0.1392 (1.31)
PC	-2.3028* (-1.71)		-2.0871 (-1.16)	0.0663 (0.50)	-1.9479 (-1.00)	
DB	2.9439*** (2.65)	-1.4567 (-0.21)	2.0198 (1.17)	2.6188 (1.51)	2.7350** (2.15)	2.1692 (1.34)
INF	-0.0427 (-0.11)	-0.1007 (-0.27)	0.2576 (0.62)	0.2735 (0.57)	0.2958 (0.75)	0.6647 (1.45)
GDPGR	0.1849* (1.70)	0.2120 (2.06)	0.1670 (1.47)	0.1802 (1.32)	0.1313 (1.26)	0.1257 (1.15)
COV	1.3207 (1.26)	2.7048** (2.49)	0.2754 (0.28)	0.8156 (0.42)	0.3222 (0.28)	-.2441 (-0.11)
Constant	2.8114** (2.24)	8.0979*** (3.49)	2.6602 (0.88)		5.0839 (0.98)	
Obs.	378	378	378	340	378	340
Groups	38	38	38	38	38	38
Instruments			36	27	36	39
AR (1) (p-value)			0.044**	0.036	0.009***	0.006***
AR (2) (p-value)			0.732	0.947	0.710	0.969
Hansen			0.394	0.103	0.394	0.103

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

Table 5.6: The full sample profitability model including all variables with ROAE as the dependent variable using all estimators.

Variables	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
	(1)	(2)	(3)	(4)	(5)	(6)
$ROAE_{t-1}$	0.2700^{***} (6.22)	0.0900^{**} (1.89)	0.2255^{***} (2.68) {0.084}	0.2247^{**} (2.24) {0.100}	0.2370^{**} (2.43) {0.097}	0.1776^{**} (1.84) {0.096}
$SIZE_{t-1}$	-0.5885^{*} (-1.82)	-3.9997^{***} (-3.54)	-0.2122* (-0.39)	-2.0199* (-1.07)	-0.4816* (-1.06)	-2.0664* (-1.20)
NPL_{t-1}	0.0069(0.32)	-0.1981^{***} (-4.76)	-0.0488 (-1.57)	-0.3072^{**} (-2.07)	-0.0523 (-1.44)	-0.3222^{***} (-3.00)
$LOANGR_{t-1}$	0.6295 (0.68)	-2.4944^{**} (-2.14)	0.3948 (0.35)	-0.9299 (-0.50)	0.3815 (0.39)	-1.4260 (-1.21)
FGR_{t-1}	6.0396^{***} (2.74)	2.9386 (1.33)	8.0133 (1.04)	4.7176 (1.13)	2.5617 (1.55)	5.1934^{*} (1.81)
LCR_{t-1}	-0.0289 (-0.43)	0.0465 (0.32)	-0.0144 (-0.38)	0.0309 (0.60)	-0.0309 (-1.13)	0.0161 (0.31)
$NSFR_{t-1}$	0.0408 (0.48)	-0.0558 (-0.31)	0.0261 (0.57)	-0.0263 (-0.36)	0.0448 (1.31)	-0.0063 (-0.09)
ETR_{t-1}	0.3585 (0.73)	0.1890 (0.40)	0.0085 (0.03)	0.1794 (0.29)	0.1162 (0.46)	0.4308 (1.11)
$LOAN_{t-1}$	0.0520^{***} (1.60)	-0.6858 (-1.11)	-2.1920 (-1.05)	-1.0759 (-0.92)	-1.9198 (-1.53)	-1.2438 (-1.49)
DEP_{t-1}	-1.6533^{***} (-2.73)	1.5682 (1.30)	2.3812 (1.06)	6.5973 (1.05)	2.9841 (1.54)	2.2612^{*} (1.66)
OE_{t-1}	0.6793^{***} (2.75)	-0.1413^{***} (-9.23)	-0.1525^{***} (-5.27)	-0.1507^{***} (-3.02)	-0.1506^{***} (-5.42)	-0.1447^{***} (-3.93)
MC	-71.4246 (-3.22)	-0.0372 (-0.53)	0.0748 (1.27)	0.0445 (0.45)	0.1045 (1.42)	0.1145 (1.04)
PC	-0.1401 (-11.07)		-1.3778 (-0.67)		-1.7415 (-0.92)	
DB	0.0288^{***} (0.42)	-3.0308 (-0.43)	2.1556 (1.13)	2.3307 (1.36)	2.9220^{**} (2.04)	1.3060 (0.78)
INF	-2.1196 (-1.54)	-0.1431 (-0.38)	0.4287 (0.97)	0.2384 (0.43)	0.2318 (0.54)	0.5955 (1.18)
GDPGR	3.0631^{**} (2.69)	0.2483^{**} (2.37)	0.1408 (1.41)	0.2042 (1.51)	0.1641 (1.56)	0.1646 (1.46)
COV	-0.0861 (-0.22)	2.5761^{**} (2.33)	0.1691 (0.20)	0.6349 (1.00)	0.2236 (0.19)	0.1980 (0.09)
Constant	0.2133^{**} (1.91)	5.0357^{***} (3.67)	1.9610 (0.59)		6.5273 (1.03)	
Obs.	378	378	378	340	378	340
Groups	38	38	38	38	38	38
Instruments			36	27	36	27
AR (1) (p-value)			0.029^{**}	0.018^{**}	0.006^{***}	0.003^{***}
AR (2) (p-value)			0.636	0.937	0.592	0.985
Hansen			0.315	0.099	0.315	0.099

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

Table 5.7: The full sample profitability model including all variables with NIM as the dependent variable using all estimators.

Variables	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
	(1)	(2)	(3)	(4)	(5)	(6)
NIM_{t-1}	0.8331^{***} (28.59)	0.5892^{***} (13.03)	0.9528^{***} (8.55)	0.6197^{***} (3.53)	0.8778^{***} (7.66)	0.5941^{***} (3.67)
			{0.111}	{0.175}	{0.114}	{0.161}
$SIZE_{t-1}$	-0.0146 (-0.57)	-0.1638^{*} (-1.90)	-0.0223* (0.60)	-0.2775 (-1.39)	-0.0093 (-0.19)	-0.2487 (-1.61)
NPL_{t-1}	0.0024 (-1.53)	-0.0058^{*} (-1.84)	-0.0024^{*} (-1.81)	-0.0049^{*} (-1.85)	-0.0027^{*} (-1.83)	-0.0045^{**} (-1.99)
$LOANGR_{t-1}$	0.3612^{***} (5.22)	0.1115 (1.23)	0.3873^{***} (2.61)	0.1230 (1.10)	0.3337^{**} (2.46)	0.0593 (0.57)
FGR_{t-1}	5.3367^{***} (3.60)	1.9389^{**} (2.52)	3.2308 (1.65)	3.3316 (0.44)	5.0768 (1.42)	3.2042 (1.14)
LCR_{t-1}	-0.0107^{**} (-2.03)	0.0094 (0.86)	-0.0028 (-0.56)	0.0041 (1.12)	-0.0075 (-1.45)	0.0064 (1.63)
$NSFR_{t-1}$	0.0147^{**} (2.21)	-0.0111 (-0.80)	0.0042 (0.63)	-0.0043 (-0.86)	0.0105 (1.52)	-0.0076 (-1.43)
ETR_{t-1}	0.0214 (0.58)	00.0034 (0.09)	0.0008 (0.04)	-0.0217 (-1.08)	-0.0046 (-0.21)	-0.0108 (-0.47)
$LOAN_{t-1}$	-0.1594^{***} (-3.53)	-0.1110^{**} (-2.36)	-0.2311 (-1.66)	-0.0701 (-0.42)	-0.1885 (-1.41)	-0.1437 (-1.08)
DEP_{t-1}	6.4174^{***} (3.64)	2.6381^{***} (2.67)	1.2855^{*} (1.66)	7.8157 (0.47)	9.2077 (1.44)	5.6794 (1.19)
OE_{t-1}	-0.0020^{**} (-2.53)	-0.0016 (-1.47)	-0.0007 (-0.95)	-0.0011 (-1.12)	-0.0016^{*} (-1.74)	-0.0017 (-1.57)
MC	0.0059 (1.16)	-0.0030 (-0.56)	0.0100 (1.76)	0.0042 (1.21)	0.0115^{**} (2.23)	0.0017 (0.47)
PC	-0.0085 (-0.08)		0.1552 (0.98)		0.0318 (0.16)	
DB	0.0977 (1.09)	-0.0332 (-0.06)	-0.0294 (-0.23)	0.2467 (1.59)	0.0361 (0.21)	0.2313 (1.32)
INF	-0.0447 (-1.52)	-0.0580^{**} (-2.00)	-0.0203 (-0.61)	-0.0235 (-1.01)	-0.0220 (-0.62)	-0.0567 (-1.00)
GDPGR	0.0057 (0.69)	0.0069 (0.87)	-0.0004 (-0.03)	0.0000 (0.01)	0.0027 (0.27)	0.0068 (0.59)
COV	-0.1211 (-1.50)	-0.0250 (-0.30)	$-.2019^{*}$ (-1.96)	-0.0320 (-0.33)	-0.1731^{*} (-2.03)	-0.0829 (-0.75)
Constant	0.0938 (0.11)	4.2075^{*} (1.93)	-1.1407 (0.95)		-0.3139 (-0.20)	
Obs.	378	378	378	340	378	340
Groups	38	38	38	38	38	38
Instruments			36	27	36	24
AR (1) (p-value)			0.004^{***}	0.045^{**}	0.014^{**}	0.014^{**}
AR (2) (p-value)			0.096	0.059	0.106	0.071
Hansen			0.464	0.536	0.464	0.536

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

5.6 The determinants of bank profitability before and after Brexit

Brexit refers to the UK's exit process from the European Union, shaped by the 2016 referendum. The process of Brexit started in June 2016, when voters in the United Kingdom determined to leave the European Union, and it is scheduled to end in October 2019 with the definitive withdrawal of the UK from the EU. According to Tata (2018) and Shahzad et al. (2019), the exceptional situation of Brexit in 2016 has created new uncertainties already affecting the UK and EU economies. Fernández, Paz-Saavedra and Coto-Millán (2020) add signs of investment losses and productivity decline during Brexit. The banking sector is sensitive to such an event as part of the financial system.

Using data from a sample of 34 banks in the UK from 2009 to 2018, Lu, Lu and Lv (2021) investigated the association between exchange rate and bank profitability after Brexit. Their results indicate that Brexit negatively affects both ROA and ROE. Also, there is no correlation between bank performance and the exchange rate during Brexit. Still, the research period covers just two years since the beginning of Brexit, so the findings remain debated.

To stand on the effect of Brexit on the determinants of the UK commercial banks' profitability, the sample in this research was divided into two sub-samples, pre-Brexit and post-Brexit, for comparison. The pre-Brexit sample included data from 35 UK commercial banks from 2010 to 2015, giving 150 observations. The post-Brexit sample included data of 38 UK commercial banks from 2016, the year of Brexit, to 2021gining a total of 190 observations. The difference between the sample sizes is due to the bank's establishment year and the availability of annual financial data.

5.6.1 Regression analysis of the sub-samples (pre and post-Brexit) for all profitability models

The profitability models were first analysed using the GMM estimators for consistency with the total sample analysis. However, the results of GMM estimators were not valid as all lagged dependent variables for all profitability proxies were found insignificant. Also, the number of instruments exceeds the number of groups in all GMM estimators.

For these reasons, the OLS estimator's results will be presented for inference as an alternative to GMM estimators. Table 5.8 and Table 5.9 present the results for all profitability models using the same set of independent variables used in the analysis of the whole sample except the macroeconomic variable (COV), as its inclusion in the post-Brexit sample will affect the results and make it challenging to be compared with the pre-Brexit sample results.

The coefficients on the lagged dependent variables $ROA_{t-1,}$ $ROAA_{t-1}$, ROE_{t-1}, $ROAE_{t-1,}$ and NIM_{t-1} are between 0 and 1 for all estimators, implying that bank profitability persists over time for all those with coefficients between 0 and 1. As shown in Table 5.8, the pre-Brexit sample analysis results show that the bank-specific variable SIZE coefficients are significant and negatively associated with all profitability models. The coefficients are significant at 0.05 level for ROA and ROAA, while at 0.01 for ROE, ROAE, and NIM. However, these significant associations do not appear in the results of the post-Brexit sample analysis, as presented in Table 5.9.

The results for ROA and ROAA models, in Table 5.8 and Table 5.9, show that variables NPL, FGR, LOAN, DEP, OE, and DB are determinants of the UK commercial bank profitability for all mentioned variables maintained the same significance level during the two periods. The coefficients are 0.10 for NPL and DB, 0.05 for FGR, LOAN, and DEP, and 0.01 for OE. For ROE and ROAE models, the results show that variables OE and DB are significant determinants of the UK commercial bank profitability for the pre and post-Brexit samples. The variables maintain the same level of significance, being at 0.01 level. These negative coefficients on OE indicate that UK commercial banks need to focus more on their operation expenses and keep them at an optimal level that does not affect their operations income. Regarding the DB, the positive coefficients indicate that UK domestic commercial banks are more profitable than foreign banks during the study period.

For the pre-Brexit data analysis, the results in Table 5.8 show that the ETR is negatively associated with both ROE and ROAE, indicating that the increase in total taxes decreased the bank's profitability. The coefficients on ROE and ROAE are at the 0.10 level. However, the results of these profitability measures are insignificant for the post-Brexit data analysis, as presented in Table 5.9. The negative significant coefficients of PC at 0.01 for ROE and ROAE of pre-Brexit data analysis indicate that the privately-owned UK commercial banks are less profitable than the publicly quoted banks. However, the post-Brexit data analysis results, presented in Table 6.9, provide an opposite sign but are found insignificant for both profitability measures.

The coefficients on the NIM as the fifth profitability measure show notable results. For the pre-Brexit data analysis, it is found that the Liquidity ratio, measured by the FGR, has a positive significant association with NIM at 0.01 level. This result indicates that the increase in net loans over the total deposits of the UK commercial banks led to an improvement in their profitability due to increasing their net interest income. Also, it is found that the Basel III ratios, measured by the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), are significant determinants of the UK commercial banks' NIM, as presented in Table 5.8. In contrast, all variables are found insignificant for the post-Brexit data analysis, as shown in Table 5.9.

Table 5.8: The Pre-Brexit sample profitability model includes all variables with ROA, ROAA, ROE, ROAE and NIM as the dependent variables using the OLS estimator.

	(OLS)				
Variables	(ROA)	(ROAA)	(ROE)	(ROAE)	(NIM)
ROA_{t-1}	0.3085*** (5.09)				
$ROAA_{t-1}$		0.3383*** (5.77)			
ROE_{t-1}			0.3937*** (5.78)		
$ROAE_{t-1}$				0.3886*** (6.15)	
NIM_{t-1}					0.7788*** (14.20)
$SIZE_{t-1}$	-0.1172** (-2.39)	-0.1043** (-1.88)	-0.8805*** (-3.39)	-0.1400*** (-3.74)	-0.1646*** (-2.99)
NPL_{t-1}	0.0030* (1.84)	0.0032* (1.68)	0.0191 (1.10)	0.0214 (1.19)	0.0002 (0.13)
$LOANGR_{t-1}$	0.0447 (0.42)	0.0014 (0.01)	0.3233 (0.32)	-0.6587 (-0.63)	0.0261 (0.30)
FGR_{t-1}	0.9885** (2.14)	0.8271** (2.12)	0.8541 (0.95)	0.2057 (1.63)	0.8050*** (3.02)
LCR_{t-1}	-0.0077 (-0.47)	-0.0091 (-0.49)	-0.1322 (-0.77)	-0.1770 (-0.99)	-0.0438** (-2.51)
$NSFR_{t-1}$	0.0101 (0.50)	0.0120 (0.52)	0.1606 (0.75)	0.2151 (0.97)	0.0548** (2.52)
ETR_{t-1}	-0.0329 (0.84)	-0.0338 (0.75)	-0.7327* (1.79)	-0.7849* (1.86)	-0.0393 (1.07)
$LOAN_{t-1}$	-0.6824** (-2.12)	-0.7792** (-2.10)	-3.1775 (-0.94)	-5.6086 (-1.62)	-0.8970*** (-2.98)
DEP_{t-1}	0.1877** (2.12)	0.9191** (2.10)	0.8235 (0.94)	0.5758 (1.61)	0.5651*** (3.01)
OE_{t-1}	-0.0112*** (-8.74)	-0.0133*** (-8.52)	-0.0876*** (-7.02)	-0.0831*** (-6.35)	-0.0015 (-1.49)
MC	0.0224 (0.79)	0.0349 (1.07)	0.0152 (0.05)	0.0137 (0.04)	-0.0129 (-0.49)
PC	-0.3486 (-1.71)	-0.2518 (-1.09)	-0.2889*** (-3.15)	-0.4772*** (-3.17)	-0.6009** (-2.45)
DB	0.3192* (1.74)	0.3797* (1.80)	0.4100*** (1.75)	0.3301*** (2.14)	0.3968** (2.12)
INF	-0.0600 (-0.70)	-0.0452 (-0.46)	0.1922 (0.21)	0.0687 (0.07)	-0.0255 (-0.31)
GDPGR	0.1178 (0.85)	0.1729 (1.09)	1.5818 (1.10)	1.6070 (1.08)	0.1435 (1.12)
Constant	2.6438 (1.13)	1.5042 (0.56)	4.1248** (2.10)	6.28755** (2.27)	4.7513** (1.99)
Obs.	150	150	150	150	150
R^2	0.798	0.826	0.719	0.736	0.920
Adj R^2	0.770	0.802	0.680	0.700	0.909
F-Statistic	28.86 {0.0000}	34.66 {0.0000}	18.63 {0.0000}	20.32 {0.0000}	83.75 {0.0000}

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

Table 5.9: The Post-Brexit sample profitability model includes all variables with ROA, ROAA, ROE, ROAE and NIM as the dependent variables using the OLS estimators.

	(GMM)				
Variables	(ROA)	(ROAA)	(ROE)	(ROAE)	(NIM)
ROA_{t-1}	0.2274^{***} (3.85)				
$ROAA_{t-1}$		0.2302^{***} (4.00)			
ROE_{t-1}			0.0474^{***} (0.75)		
$ROAE_{t-1}$				0.0659^{***} (1.06)	
NIM_{t-1}					0.9024^{***} (20.84)
$SIZE_{t-1}$	-0.0276 (-0.93)	-0.0335 (-1.08)	-0.3214 (0.84)	-0.2794 (0.73)	-0.0014 (-0.04)
NPL_{t-1}	-0.0063^{**} (-2.12)	-0.0071^{**} (-2.27)	0-.0339 (-0.85)	-0.0251 (-0.63)	-0.0138 (-4.21)
$LOANGR_{t-1}$	0.0277 (0.22)	0.1624 (1.26)	0-.9763 (-0.61)	-0.5848 (-0.36)	0.2061 (1.53)
FGR_{t-1}	0.0395^{**} (2.38)	0.3713^{**} (2.40)	0.0982^{**} (-0.97)	0.1684^{***}(2.97)	0.4501 (0.84)
LCR_{t-1}	-0.0081 (-1.37)	-0.0080 (-1.29)	-0.0496 (-0.63)	-0.0595 (-0.76)	-0.0077 (-1.15)
$NSFR_{t-1}$	0.0112 (1.51)	0.0111 (1.44)	0.0726 (0.74)	0.0855 (0.87)	0.0104 1.23)
ETR_{t-1}	-0.0340 (-0.59)	-0.0434 (-0.72)	-0.0562 (0.07)	-0.1709 (-0.23)	-0.0276 (-0.43)
$LOAN_{t-1}$	-0.2397^{**} (-2.38)	-0.2530^{**} (-2.40)	-0.2970^{**} (-2.48)	-0.9653^{***} (-2.99)	-0.0937 (-0.84)
DEP_{t-1}	0.2852^{**} (2.41)	0.5737^{**} (2.43)	0.8710^{**} (2.51)	0.9299^{***} (3.02)	0.6625 (0.87)
OE_{t-1}	-0.0134^{***} (7.86)	-0.0140^{***} (-7.77)	-0.1936^{***} (-8.78)	-0.1861^{***} (-8.44)	-0.0016 (-0.94)
MC	-0.0100 (-0.39)	-0.0167 (-0.62)	-0.1156 (-0.34)	-0.1252 (-0.37)	0.0017 (0.06)
PC	-0.0223 (-0.18)	-0.0134 (-0.10)	1.0594 (0.64)	1.3505 (0.82)	0.03312 (0.23)
DB	0.1612^{*} (1.66)	0.2353^{*} (2.31)	0.6656^{***} (2.09)	0.4614^{***} (1.93)	0.0474 (0.41)
INF	0.1206 (1.02)	0.1361 (1.10)	0.8731 (0.56)	1.1170 (0.72)	0.1850 (1.43)
GDPGR	-0.0009 (-0.05)	-0.0053 (-0.27)	0.0551 (0.22)	0.0349 (0.14)	-0.0293 (-1.40)
COV	0.0658 (0.26)	0.1002 (0.37)	1.5342 (0.45)	1.7247 (0.51)	-.1656 (-0.58)
Constant	1.3123 (0.83)	1.6634 (1.00)	5.4244 (0.26)	6.3429 (0.31)	-1.2077 (-0.69)
Obs.	190	190	190	190	190
R^2	0.663	0.678	0.529	0.540	0.923
Adj R^2	0.626	0.642	0.506	0.518	0.914
F-Statistic	17.66 {0.0000}	18.89 {0.0000}	10.06 {0.0000}	10.51{0.0000}	107.55 {0.0000}

Note: See notes to Table 5.2 for variables and Table 5.3 for the other descriptions.

5.7 Summary

This chapter presents the econometric results, including the descriptive statistics, the test for multicollinearity, and regression analysis using the OLS, FE, and GMM models. Although many studies investigate the bank profitability in the banking sector for several countries, little research sheds light on the UK banking sector over the last decade. Therefore, this research aimed to investigate the profitability of UK commercial banks and provide refreshed evidence to the existing literature. To this end, this research has been directed to investigate the association between the UK commercial banks' profitability (Return on assets, return on average assets, return on equity, return on average equity, and net interest margin as proxied by ROA, ROAA, ROE, ROAE, and NIM, respectively) and the presumed internal and external explanatory variables. Thirty econometric models (one model of OLS and FE and four GMM models for each proxy of profitability) were used based on an unbalanced panel dataset of 38 domestic and foreign commercial banks operating in the UK banking sector from 2010 to 2021. Also, the period of this study has been divided into two groups, presenting the pre and post-Brexit as sup-samples to investigate the determinants of the UK commercial banks' profitability, applying and presenting the results of the OLS estimator as an alternative of the GMM estimators due to the invalidity of GMM results of the sub-samples.

To the best of the author's knowledge, this is the first research to investigate the determinants of profitability of the UK commercial banks using the OLS, FE, and GMM (employing the (system) and (difference) estimators with both (one-step) and (two-step)) procedures. The general significance of the lagged dependent variable in the results of regressions in this research, for the whole and pre and post-Brexit samples, suggests the need to account for dynamic effects and justifies using such estimators. This research also extends the previous literature by considering additional factors, such as Basel III ratios and COV, not employed in previous studies of UK commercial bank profitability. The current results use a larger sample of the number of banks and periods compared to any previous analysis of the UK banking system. Also, the empirical results of this research suggest that the GMM estimator is more efficient than the OLS and FE estimators for the entire sample.

The main findings of this research are presented in Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7 for the entire sample and in Table 5.8 and 5.9 for the pre and post-Brexit samples, respectively. Based on the preferred GMM estimator for each profitability model, the results show that bank-specific variables, SIZE, NPL, LOANGR, OE, and COV, are significant determinants of UK commercial banks' profitability. For all profitability models, ROA, ROAA, ROE, ROAE and NIM, with all GMM estimators, the bank-specific variables LCR, NSFR, ETR, LOAN and the industry-specific and macroeconomics variables MC, PC, INF, GDPGR (except for ROA and ROAA), COV (except for NIM) do not appear to be determinants for UK banks profitability as the coefficients for all mentioned variables are insignificant.

Chapter 6: Literature Review on Bank Efficiency

6.1 Introduction

Banks are the backbone of the bank-based financial system as they play an essential role in economic development by acting as intermediaries to transfer funds from surplus to deficit units. The process of financial intermediation enables financial investment to be turned into actual investment, which leads to economic growth. The efficiency of banks is, therefore, a significant factor in maintaining confidence, trust, and soundness in the banking sector. So, a bank's efficiency is vital and requires to be paid more attention.

The efficient performance of banks helps them compete more effectively and survive in the financial sector. Efficient banks are also assumed to have a higher rate of return relative to cost than their inefficient counterparts and participate better in economic growth and development. Banks would be exposed to default, impairment, or insolvency risk without trust and soundness. The inefficient invariant performance of banks could also lead to a higher likelihood of bank failure that could affect the other sectors of the economy, such as agriculture, commerce, and industry (Berger and Humphrey,1997).

Efficiency has become a major contemporary issue due to increased competition, technological innovation, globalisation, and deregulation. Hence, it is crucial for banking sector regulators and market analysts to have adequate, relevant information that helps identify actual or potential problems in the banking systems and individual banks. Improving efficiency has been a challenge for the industry of financial services. Cost management is not only about reducing expenses but also about generating more revenue per cost unit.

Such information is also beneficial for comparing the competitiveness and efficiency of banking systems. The existence of significant inefficiency in the sector, in general, and in different groups of banks, in particular, provides room for structural changes and increase the competition and mergers and acquisitions to enhance the efficiency and productivity of the banking system and speed up a country's financial development and economic growth (Bonin, Hasan and Wachtel 2005; Fries and Taci 2005; Staikouras, Mamatzakis and Koutsomanoli-Filippak 2008; Huang, Chiang and Tsai 2015; Ghosh 2016; Stewart, Matousek and Nguyen 2016; Wanke, Barros and Emrouznejad 2016; Du, Worthington and Zelenyuk 2018).

This chapter provides an overview of bank efficiency literature. The remainder of the chapter is organised as follows. Section 6.2 presents the concept of bank efficiency and its drivers. Section 6.3 presents measures of banking efficiency. Section 6.4 presents a review of the previous studies on bank efficiency. Lastly, a conclusion of the whole chapter is presented in section 6.5. These sections are placed in this order to give the reader a comprehensive understanding of the term efficiency first, then bank efficiency, by highlighting this research's contribution to the existing literature. The efficiency literature review includes studies conducted using European, US, and international level samples of banks. It concludes with extended summaries that sum up the findings of past research on bank efficiency.

6.2 The concept of bank efficiency and its drivers

The term efficiency as a performance indicator for all firms was formulated in the early works of Edgeworth (1881) and Pareto (1927) and documented with its practical implementation in the book of Shephard (1953). According to Cvilikas and Jurkonyte-Dumbliauskiene (2016), efficiency is the maximum potential ratio between the output and the input of a product development process, which indicates the optimal distribution of available resources that would allow reaching the maximum potential. Drucker (1963) defines efficiency as the ability of an institution to perform its output from the minimum input level. In other words, it is a measure of effectiveness that produces the minimum waste of cost, time, effort, and skill.

Efficiency differs from effectiveness; however, both present an entity's performance. According to Jouadi and Zorgui (2014), efficiency is the idea of producing in the best manner, which means that it focuses on using minimum inputs to produce the best output—the optimised use of resources to create the best products with the minimum costs. The effectiveness concept outlines the yield of factors and the reach of the goals without considering the manner and the optimised use of resources.

Regarding the banking sector, efficiency in terms of cost minimisation and profit maximisation can be seen as supporting the implemented macroeconomic policies, which generate stable development, economic growth, and welfare for society. Banks are also seen as purchasing labour and materials and accepting deposits to create outputs of loans and investments. The intermediation approach assumes that banks act as financial intermediaries whose direct role is to accept funds from savers in exchange for their liabilities; the banks, in turn, will provide loans to others for profit-making (Chu and Lim 1998). This approach is also known as the asset approach, where financial institutions are assumed to act as intermediaries between the savers and borrowers' units.

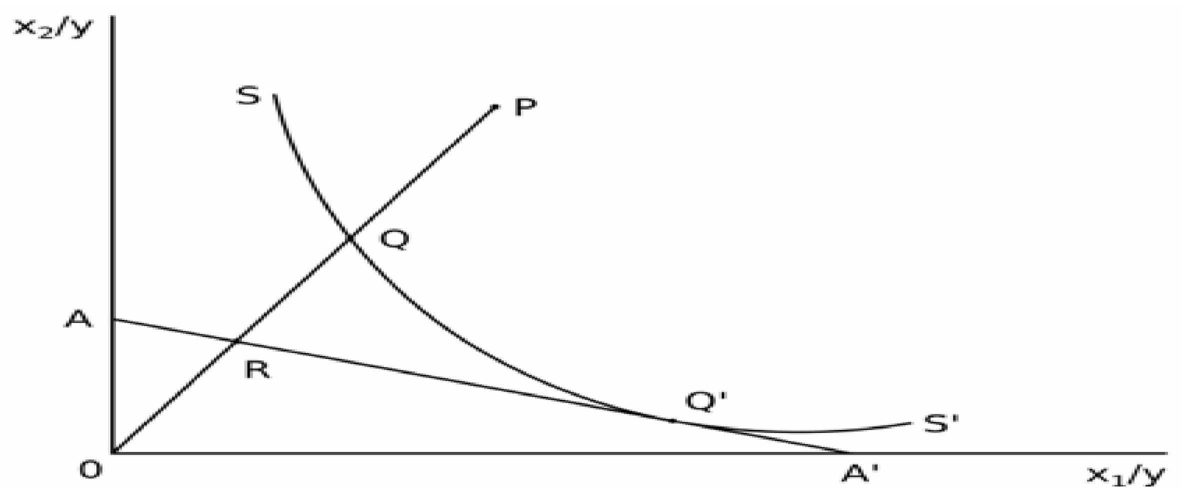
However, Berger and Humphrey (1997) argue that neither of these approaches is perfect as they cannot entirely capture the dual role of financial institutions as providers of transactions/document processing services and financial intermediaries. They also point out that intermediation may be more suitable for evaluating entire financial institutions since it includes interest expenses, which often account for half to two-thirds of total costs. Another point is that minimisation of total costs, not just production costs, is needed to maximise profits. In contrast, the production approach could be relatively better for evaluating the efficiency of bank branches. This is because branches mainly process customer documents for the institution, and branch managers generally have little effect on bank funding and investment decisions.

Diallo (2018) mentions that efficiency helps banks be more resilient to shocks, positively affecting growth. Also, bank efficiency relaxes credit constraints and increases the growth rate for financially dependent industries during crises. Waheed and Younus (2010) provide quantitative support to the assumption that the development of a financial sector is essential to economic growth and that the efficiency of the financial sector is potentially vital to the long-term growth performance of the economies.

The literature on efficiency exhibits different ways of classifying banking efficiency. Yudistira (2004) distinguishes between two primary types of banking efficiency: scale efficiency (Farell, 1957) and X-efficiency (Leibenstien, 1966). Scale efficiency is the relationship between a bank's per unit average production cost and volume. X-efficiency represents deviations from the cost-efficient frontier that depicts the lowest production cost for a given output level differently. Kablan (2010) defines X-efficiency as a measure of how well management aligns technology, human resource management, and other resources to deliver a given output level.

Farrell (1957) drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency that could account for multiple inputs. He was the first to measure efficiency empirically and divided the concept of efficiency measures into technical efficiency (TE) and allocative efficiency (AE).

Figure 6.1: Overall, Technical and Allocative Efficiency.



Source: Coelli et al. (2005, p. 52).

Figure 6.1 introduces the concept that combining two components will produce overall economic efficiency (OEE). Assuming a firm "Z" uses only two inputs, (x1) and (x2), to produce a single output (y) at point (P). The (SS') slope displays the possible combinations of inputs the firm can produce if it is perfectly efficient. The slope (AA') shows the input price ratio and the various combinations of inputs requiring the same expenditure level. If the firm's production is efficient, it should occur at point (Q'), which implies cost minimization. That is where the (SS') and (AA') slope intersect, meaning the input combinations (Q') are technically and allocative efficient. As the "Z" firm produces using the combination of input at point (P), two types of inefficiency appear. First, it is technically inefficient since moving to point (Q) could produce the same output with fewer inputs. To measure the magnitude of a firm's technical efficiency (TE), the ratio is calculated as (OQ/OP), which is equal to (1 - QP/OP).

Second, it is allocative inefficient. Producing at point (P) demonstrates that the firm made an incorrect choice regarding the combination of inputs at the given prices, incurring more cost than if it had produced at point (Q'). According to Farrell (1957), the Overall Efficiency (OE) equals Technical Efficiency (TE) multiplied by Allocative Efficiency (AE) (OE =(OQ/OP) * (OR/OQ)). The allocative efficiency (AE) is measured as a ratio of (OR/OQ) calculations. Then, measuring the Overall Efficiency (OE) can be done since the calculations of the ratios for TE and AE are available.

Coelli et al. (2005) point to another way of classifying banking efficiency based on the following five types: 1) Pure technical efficiency: The effectiveness with which a given set of inputs is used to produce an output. Banks' technical efficiency is the difference between the observed quantity of input and output variables concerning the optimal quantity of input and output variables. An efficient bank can achieve a maximum value of one compared to an inefficient bank, which can be reduced to zero. 2) Scale efficiency: The ability of a bank to reach optimal operations. A bank has scale efficiency when operating in constant returns to scale. 3) Allocative efficiency: It measures a bank's success in selecting an optimal set of inputs with a given set of input prices. 4) Cost efficiency: a bank's ability to provide services without wasting resources due to technical or allocative inefficiency. 5) Scope efficiency: This type appears when a bank operates in different diversified locations. In their (2000) study, Harker and Zinos set the drivers of bank efficiency into three main groups that, from their point of view, represent the engine of banking success. These groups of bank efficiency are the strategy, the execution of strategy, and finally, the environment.

Banks face numerous strategic choices about product mix, client mix, geographical location, distribution channels, and institution form. These choices define how the banks provide their services to customers and underline the financial risk banks are willing to face. A successful strategic decision concerning client mix hinges upon matching a targeted client segment with well-priced products. The Execution of Strategy refers to the tools used to apply strategies. A strategy can be executed through human resource management, technology, and process design.

Regarding the definition of X-efficiency stated in Section 6.2, X-efficiency can be used to evaluate the implementation of the bank strategy. Concerning the Environment, banks attempt to influence environmental factors through marketing efforts, research, and development. According to Kablan (2010), these environmental factors include information technology, client tastes, and regulations.

6.3 Measures of banking efficiency

6.3.1 Structural and Non-structural Measures

Hughes and Mester (2008) assume that the typical approaches to measuring bank efficiency are structural and non-structural. According to their study, the structural approach, also known as "technical efficiency", depends on a theoretical model of the banking firm and an optimisation concept. This approach assumes that a bank as a financial intermediary produces informational intensive financial services, diversifies risks, and connects the theory of financial intermediation with the microeconomics of bank production. This helps the bank's production structure's choice of outputs and inputs.

The non-structural approach compares performance among banks using different financial ratios. It aims to evidence agency problems in correlations with performance ratios and variables characterising the quality of banks' governance. It also considers the relationship between performance on one side and investment strategies and governance characteristics on the other side.

The structural approach brought a disagreement about the exact banks' output. Berger and Humphrey (1992) state three common approaches to defining a bank's output. First is the asset approach for defining a bank's output. This approach defines a bank as a financial intermediary between liability holders and the receivers of bank funds. Therefore, loans and other assets express the bank outputs, while deposits and liabilities are the inputs.

The second is the user cost approach. The user cost approach uses a net contribution to bank revenue to identify whether a financial product is an input or output. This means that if the financial returns on an asset exceed the opportunity cost of funds or the financial costs of liability are less than the opportunity cost, the instrument is considered a financial output. Otherwise, the instrument is considered a financial input. The user cost approach defines whether an asset or liability classification contributes to a bank's financial output.

Lastly is the value-added approach. The approach supposes that all liability and asset categories have some output characteristics. It differs from the two previously stated approaches in that it does not distinguish inputs from outputs mutually exclusive. A significant difference between this approach and the user cost approach is that the value-added approach straightforwardly utilises operating cost data rather than implicitly determining these costs.

6.3.2 The Traditional, Parametric, and Non-Parametric Measures

Wozniewska (2008) classifies the methods of measuring efficiency into three principal groups: The Traditional, Parametric, and Non-Parametric Methods. According to Tuskan and Stojanovic (2016), the traditional method of measuring efficiency uses ratio analysis from several financial institutions. This analysis is done by calculating numerous accounting ratios, providing a measurement of the financial soundness of financial institutions and the operating efficiency of their management. According to this method, financial statements are the primary source of accounting information used to measure a financial institution's operating efficiency.

The parametric method, known as "parametric programming", is generally concerned with the production or expense function base. It is used to estimate the characteristics of the function and measure economies of scale with the assumption that all decision-making units (DMUs) operate efficiently. According to Tuskan and Stojanovic (2016) and Burger and Humphrey (1997), parametric methods can be classified into three different categories: The Stochastic Frontier Approach (SFA), The Thick Frontier Approach (TFA), and The Distribution-Free Approach (DFA).

SFA was first proposed by Aigner, Lovell and Schmidt (1977) and then developed by Greene (1990), Mester (1996), and Bauer et al. (1998). The technique utilises statistical techniques to estimate efficiency relative to the estimated frontier. In contrast to the deterministic statistical frontier approach and in line with the typical non-frontier approach to estimating economic relationships, the SFA approach allows the frontier to be stochastic. SFA specifies a function for cost, profit, or production to determine the frontier and treats the residual as a comprise error comprising (i) random error with a symmetric distribution – often typical; (ii) inefficiency with an asymmetric distribution – often a half-normal because inefficiencies will never be a plus for production or profit or a negative for the cost (Mathews and Thompson 2008).

TFA uses the same functional form for the frontier cost function as SFA, but it is based on a regression estimated using only the best performers in the data set. That is, those in the lowest average-cost quartile for their size class. Parameter estimates from this estimation are then used to obtain estimates of best-practice costs for all the firms in the data set (Bauer et al. 1998). According to Mathews and Thompson (2008), firms are ranked according to performance, and it is assumed that (i) deviations from predicted performance values by firms from the frontier within the highest and lowest quartiles represent random error and (ii) deviations between the highest and lowest quartiles represent inefficiencies.

DFA specifies a functional form for the cost function, as do SFA and TFA, but DFA separates inefficiencies from random error differently. It does not impose a specific shape on the efficiency distribution as TFA. Instead, DFA presumes that each firm has a core efficiency or average efficiency, constant over time, while random error tends to average over time. Unlike other approaches, a panel data set is required; thus, only panel efficiency estimates over the entire time interval are available (DFA-P) (Bauer et al. 1998).

The non-parametric method is also known as the "non-parametric programming approach". Charnes, Cooper and Rhodes (1978) assessed the non-parametric methods as the methods that use decision-making units' efficiency frontiers to construct efficiency measures. The approach considers the ranking of efficiency scores of DMUs and the degree to which total efficiency in the financial sector can be improved. This efficiency measurement is derived from data analysis from DMUs for defining productive units characterised by multiple typical outputs and commonly designated inputs.

The Data Envelopment Approach (DEA) is the most common non-parametric efficiency measure introduced by Charnes, Cooper and Rhodes (1978). They define DEA as a mathematical programming model applied to observation data that provides a new way of obtaining the empirical estimate of relations such as the production functions or efficient production possibility surface, which are considered the cornerstone of modern economics. Berger and Humphrey (1997) suggest that DEA is precious to assessing and informing government policy regarding financial institutions. Therefore, it was recommended that DEA replaces the traditional method of measuring banking efficiency mentioned previously. This approach provides an objectively determined numerical efficiency value using multiple inputs and outputs.

Because there are factors that influence efficiency but are not direct inputs or outputs to the production process, the DEA-based efficiency analysis is expanded to incorporate the impact of these environmental factors (Kondova and Bandyopadhyay, 2019). As this research applies the DEA method to investigate the bank efficiency of the UK commercial banks, more technical details and explanations of this method compared with other non-parametric methods will be presented in Chapter 7.

6.4 Review of the previous studies on bank efficiency

Banks' business performance deriving from business efficiency has appeared in considerable studies since the 1950s. Despite its long-term implications, the concept of efficiency was only presented explicitly in Lovell and Thore's (1992) study. According to Lovell and Thore (1992), an institution's business efficiency reflects the association between the output and input value compared to the minimum or maximum output value the organisation can reach. In other words, this association can be measured by comparing the observed output to the maximum output the institution achieves on a given input or by comparing the observed input with the minimal input to achieve a specific output.

Farrel's (1957) study is notable among studies on efficiency since he clarified the concept of efficiency. Not only did he specify each type of efficiency, but he also included them in a model. Farrel (1957) introduced an efficient frontier condition in which an organisation can maximise its output based on a certain amount of input. As a result, an institution's business performance includes technical, distributional, and economic efficiency.

Technical efficiency is the ability to maximise the output from a certain amount of input or to minimise the input to obtain a certain amount of output. An organisation is considered technically inefficient if it fails to produce the most significant output from a given input. In other words, the institution is producing at a point outside of the efficient frontier. According to Sufian (2011), for banks, the selections of inputs and outputs to produce the efficient frontier vary in relevant empirical research and affect the result of efficiency calculation. The combinations of input and output in earlier papers can be divided into four different approaches: production, intermediation, profit-oriented, and value-added.

The production approach, introduced by Benston (1965), uses deposits as the primary input to create bank loans. However, this approach ignores investing, a significant activity that can create value for a modern bank (Berger and Humphrey, 1997). The intermediation approach, in contrast, emphasises the association role between borrowers and lenders of banks. Thus, deposits, labour, and physical assets are inputs to produce loans and investments of a bank (Sealey and Lindley, 1977). This approach was developed as a value-added approach in which a deposit is assumed to be the bank's output because of its ability to create bank value. The profit-oriented approach assumes that the banking business is a process to achieve profit from its expenses (Drake, Hall and Simper, 2006). Therefore, to identify an efficiency frontier, inputs are interest and non-interest expenses, while outputs are interest and non-interest revenues.

The literature has extensively covered bank efficiency, including its drivers or determinants, effects, impacts, and measures. Different approaches have been utilised in evaluating banks' input and output data. These approaches were non-parametric, such as the Data Envelopment Analysis (DEA), and parametric, such as the Stochastic Frontier Approach (SFA), Distribution-Free Approach (DFA), and Thick Frontier Approach (TFA). The approaches vary in the assumptions about the shape of the frontier, the existence of random error, and (if the random error is allowed) the distributional assumptions imposed on the inefficiencies and random error to disentangle one from the other. They also differ in whether the underlying concept of efficiency is technical or allocative. The (non-parametric) DEA studies measure technical efficiency, while the (parametric) SFA, TFA, and DFA studies usually measure allocative efficiency (Ferrier and Lovell 1990; Hunter and Timme 1995; Bauer et al. 1998).

Berger and Humphrey (1997) critically reviewed 130 studies of financial institution efficiency, as applied in 21 countries, from multiple periods and various institutions, including banks, credit unions, and insurance companies. Their results indicate that progress has been made on efficiency measurement rather than explaining the differences in performance (profitability or efficiency) across institutions. They also state that the non-parametric methods generally yield slightly lower mean efficiency estimates and seem to have a more excellent dispersion than the results of the parametric models. Athanassopoulos and Giokas (2000) analysed 47 Greek commercial bank branches and utilised the DEA results to implement the proposed changes in the bank performance measurement system.

Casu and Girardone (2005) compared parametric and non-parametric estimations of competition, concentration and efficiency change in European banking and found that the competing methodologies do not yield markedly different results in identifying the main components of productivity growth. Bauer et al. (1998) presented a set of consistent conditions that the frontier should meet to be more beneficial for regulatory analysis and other objectives by evaluating and comparing estimates of US bank efficiency.

Soteriou and Zenios (1997) suggest that analysing banks' efficiency should include branches, service quality, operations, and profitability. They design a framework for combining strategic and efficiency benchmarking of the services offered by bank branches by using 3 DEA models: an operational efficiency model, a quality efficiency model, and a profitability efficiency model. The empirical results exhibit that superior insight can be obtained by analysing service quality, operations, and profitability jointly than the information obtained from benchmarking studies of these three dimensions separately.

Aly et al. (1990) utilised the Constant Return to Scale (CCR) model to estimate the technical, purely technical, allocative, and scale efficiencies of 322 USA banks for 1986. The number of full-time staff, fixed assets, capital, and loanable funds were chosen as inputs, while real estate loans, commercial and industrial loans, consumer loans, miscellaneous loans, and current deposits were chosen as outputs. They constructed separate efficiency frontiers to test the effect of branching. Their results show a low level of overall efficiency. The primary source of inefficiency was technical rather than allocative. Regardless, the distributions of efficiency measures for branching and non-branching banks were not found to be different.

Andersen and Petersen (1993) presented a ranking DEA model that demonstrates how much the unit can "get worse" but still be efficient. They conclude that superefficient units are those with an efficiency of over 100%; the most efficient is the highest-ranked one, while the units with an efficiency of less than 100% are inefficient and, therefore, ranked lower. In an investigation of the influence of the environment on determining the banking efficiency of the French and Spanish banking industries, Dietsch and Lozano-Vivas (2000) demonstrate that environmental variables contribute significantly to the difference in these two countries' efficiency scores.

Sathye (2003) analysed bank efficiency in India using (DEA) based on two models. The inputs in the first model were interest expenses, non-interest expenses, and outputs: net interest income and net non-interest income, while the second model inputs were deposits, employees, and outputs: net loans and non-interest income. Sathye finds that the public sector banks have a higher mean efficiency score than the private sector and foreign commercial banks. The study suggests that decreasing non-performing assets and rationalising staff and branches may continue to obtain efficiency gains and make banks more competitive internationally.

Using a sample comprising more than 4200 observations of Italian cooperative banks over the period 1997 to 2009, Fiordelisi and Mare (2013) indicate that higher efficiency levels (both in cost minimisation and revenue and profit maximisation) have a positive and statistically significant link with the probability of survival of cooperative banks. They also find that capital adequacy reduces the probability of default, supporting the view that higher capital buffers provide additional loss absorbency and reduce moral hazard problems. Sherman and Gold (1985) analysed 14 USA bank branches by applying DEA and using employees by branch, cost of space and expenses as inputs, and the number of transactions in each branch as outputs. They conclude that DEA is a beneficial complement to other techniques for improving bank branch efficiency.

Seiford and Zhu (1999) followed the intermediation approach to evaluate the 55 largest US banks and to identify the most efficient in terms of profitability and marketability. They used a two-stage model for their analysis. In the first stage: the number of employees, total assets, and shareholders' equity were used as inputs, while profits and revenue were used as outputs. In the Second stage, profits and revenue are used as inputs, market value, total return to shareholders, and earnings per share as outputs. Their findings indicate that approximately 90% of banks were inefficient regarding profitability and market value. Also, the size of the bank has decreasing returns of scale regarding the market value and positive returns of scale related to profitability. Using the same variables for inputs and outputs and applying the two stages: CCR input-oriented and BCC input-oriented models, Luo (2003) analysed technical efficiency, pure technical efficiency, and scale efficiency regarding the profitability and marketability of 245 US banks. The results indicate that banks' geographical location seems unrelated to either profitability or marketability efficiency. Also, the profitability performance's overall technical efficiency (OTE) can predict the likelihood of bank failures.

Becker, Lunardi and Macda (2003) conducted a study on the relative efficiency of Brazilian banks, considering investments made in IT. Using the BCC input-oriented model and the IT investments, personnel expenses, expenses with the physical structure, and administrative expenses as inputs, while net revenues from financial intermediation, service provision, and international operations as outputs, the results conclude that banks that invested more in IT were more efficient globally. Furthermore, foreign banks were the most efficient in the study sample.

Svitalkova (2014) followed the intermediation approach to analyse the efficiency of banks in different countries within the EU and identify the origins of inefficiency. The study applied the CCR and BCC models with and without the undesired output. The expenses with personnel, fixed assets, and deposits were used as inputs, while loans and net interest income as output and provision for credit losses (PCL) were used as undesirable output. The study concluded that the efficient countries varied considerably according to the model. Also, banks in all countries should focus on increasing lending while ensuring that PCL does not grow.

Stewart, Matousek and Nguyen (2016) followed the intermediation approach to analyse the efficiency of the Vietnamese banking system from 1999 to 2009 by identifying the determining variables for bank efficiency using a two-stage model (DEA). They used the number of employees, deposits from other banks, and client deposits as inputs, while loans from customers, other loans, and securities as outputs. Their findings indicate that the largest banks were more efficient than the medium and small banks, with small banks being the most inefficient. Also, concerning global efficiency, private banks were more efficient than state-owned banks.

Kamarudin et al. (2017) examined the Islamic banks in Southeast Asian countries by verifying specific banks, industry, and macroeconomic factors influencing productivity and efficiency. They utilised a two-stage model BCC with Malmquist and panel regressions. The inputs were personnel expenses, deposits, and fixed assets, while the Loans and investments were used as outputs. The findings of this study show that the efficiency of Islamic banks increased during the analysed period. Furthermore, capitalisation, liquidity, and world financial crises significantly influence the productivity level of Islamic banks.

To the best of the author's knowledge, few studies have been directed to investigate the efficiency of the UK banking sector as a single country-focused study using static DEA analyses. Drake (2001) used a panel data sample covering the leading UK banks from 1984 to 1995 to investigate relative efficiencies within the sector. The study used two models where the input and output selections differ based on considering deposits as input (the intermediation approach) or output (the production approach). In model 1, fixed assets, the number of employees, and deposits were used as inputs, while loans, liquid assets, investments, and other income were used as outputs. Model 2 used the same inputs and outputs but considered deposits as output. The results show that increasing returns to scale are evident for smaller banks, while the UK's "big four" clearing banks exhibit strong evidence of decreasing returns to scale throughout the sample period. Also, exceptionally large banks were found to be more X-efficient than their smaller competitors. Using alternative input/output specifications does not produce significant differences in the scale efficiency results.

In line with Drake (2001), Webb (2003), by applying the intermediation approach, reinvestigated the bank efficiency using data from the largest eight retail banks operating in the UK during the transition from 1982–1995. The inputs utilised in the study were the level of deposits, the cost of attracting those deposits, interest expense, and operational expenses, representing measures for labour, capital, and operating costs. The outputs were total income and loans, representing a bank's revenues and leading activities. The results of the DEA window analysis show that the mean inefficiency levels are low compared to the past study (Drake 2001). All eight banks in the study showed reduced levels of efficiency over the entire period. Also, it is found that scale inefficiencies dominate pure technical inefficiencies. Less big banks are more likely to report technical inefficiency. Lastly, during the 1990s, banks with asset levels over £105bn suffered decreasing returns to scale.

Webb, Bryce and Watson (2010) utilised DEA with a Windows approach analysis to investigate the impact of UK building society demutualisation on efficiency at the largest five commercial banks in the UK. Unlike Drake (2001) and Webb (2003), who have orientated the intermediation and production approaches in determining the inputs and outputs for the DEA model, Webb, Bryce and Watson (2010), in contrast, implemented a profit-orientated, non-parametric specification with revenue components (net-interest income, net-commission income, and total other income) as outputs and cost components (employee expenses, other non-interest expenses and loan loss provisions) as inputs. They found that scale efficiency dominates pure technical efficiency. Their results also indicate that converting building societies outperformed their bank counterparts in all areas of efficiency. Results also indicate that the level at which institutions continue to find economies of scale increased compared to previous research (Drake 2001; Webb 2003).

Tanna, Pasiouras and Nnadi (2011) used data from a sample from 17 banks operating in the UK for the period 2001- 2006 to investigate the link between the efficiency of UK banks and board structure, namely board size and composition. They used the intermediation approach and estimated an input-oriented model consisting of three inputs: fixed assets, deposits and short-term funding, and personnel expenses and two outputs: net loans and other earning assets. The DEA and regression analysis results show that a larger board size contributes to technical, allocative, cost, and profit-oriented efficiency. Also, a higher proportion of non-executive directors on the board has a robustly positive and significant impact on all efficiency measures. A summary of the critically discussed studies, including some recent works on bank efficiency showing their used models, inputs, outputs, and results, is presented in Table 6.1.

Table 6.1 summarises the critically discussed studies, including some recent works on bank efficiency.

Author(s)	Country(s)	Model	Input	Output	Results
Tanna, Pasiouras and Nnadi (2011)	UK	Two stages: DEA and regression analysis.	Fixed assets, deposits, short-term funding, and personnel expenses.	Net loans and other earning assets.	Larger board size contributes to technical, allocative, cost, and profit-oriented efficiency. Also, a higher proportion of non-executive directors on the board has a robustly positive and significant impact on all efficiency measures.
Chortareas, Girardone and Ventouri (2012)	EU countries	DEA model.	Personnel expenses, total fixed assets, deposits, and short-term funding.	Total loans, total other earning assets, and Fee-based income.	Strengthening capital restrictions and official supervisory powers can improve the efficient operations of banks. Interventionist supervisory and regulatory policies such as private sector monitoring and restricting bank activities can result in higher bank inefficiency levels.
Chortareas, Girardone and Ventouri (2013)	EU countries	Two stages: DEA and regression model combined with bootstrapped confidence intervals.	Personnel expenses, total fixed assets, and Interest expenses.	Total loans and total other earning assets.	The higher the degree of an economy's financial freedom, the higher the benefits for banks regarding cost advantages and overall efficiency. The effects of financial freedom on bank efficiency tend to be more pronounced in countries with more accessible political systems and higher-quality governance.
Svitalkova (2014)	European Union	Networking CCR and BCC with and without the undesired output.	Expenses with personnel, fixed assets, and deposits.	Loans and net interest income. As undesirable output: provision for credit losses (PCL).	The countries considered efficient varied considerably according to the model. Banks in all countries should focus on increasing lending while ensuring that PCL does not grow.
Wanke and Barros (2014)	Brazil	Two stages: DEA and regression.	First stage: Number of agencies and number of employees. Second stage: Administrative expenses and Personnel expenses.	First stage: Administrative expenses and personnel expenses. Second stage: Equity and fixed assets.	Brazilian banks tend to be more efficient in converting administrative and personnel expenses into equity and fixed assets than in managing physical and human resources. Variables related to mergers and acquisitions, size, and state-owned status are determinants of efficiency.

San-Jose, Retolaza and Pruñonosa (2014)	Spain	Two stages: DEA and regression.	Shareholders' equity, total assets, and total deposits.	Profit, risk, social contribution, number of jobs, and consumer credit.	Investment banks have overall efficiency ratios like other banks in Spain, although they are more efficient in the social aspect.
Chan et al. (2015)	Asia	Two stages: SBM and GMM.	Expenses, interest expenses, and other non-interest expenses.	Interest income from loans, investments, income from off-balance sheet activities	Government regulations should aim to increase market discipline, monitoring, and transparency; however, banking activities should have little intervention.
Curi, Lozano-Vivas and Zelenyuk (2015)	Luxembourg	GMM	Labour expenses, fixed assets, interbank deposits, and customer deposits.	Interbank loans, customer loans, and securities	A focused asset, funding, and income strategy is the most efficient business model. Branches diversified in assets, funding, and income and exploited efficiency advantages during the financial crisis.
Kwon and Lee (2015)	USA	Two stages: CCR and BPNN	First stage: Number of employees, shareholders' equity, and expenses. Second stage: Deposits, loans, and investments.	First stage: Deposits, loans, and investments. Second stage: Profit.	The proposed model helps the managerial process of decision-making.
Stewart, Matousek and Nguyen (2016)	Vietnam	Two stages: GMM using CCR and BCC with Bootstrap.	Number of employees, deposits from other banks, and client deposits.	Customer loans, other loans, and securities.	The largest banks were more efficient than the medium and small banks, with small banks being the most inefficient. As far as global efficiency is concerned, private banks are more efficient than state-owned banks.
Ouenniche and Carrales (2018)	UK	DEA-based analysis framework with a regression-based feedback mechanism.	Personnel expenses, fixed assets, equity, total interest expense, and total expenses, not including personnel expense.	Gross loans, total customer deposits, gross interest and dividend income, and total income.	Average CCR scores vary between 0.3144 and 0.6119, BCC scores between 0.5132 and 0.6976, and average SE scores between 0.667 and 0.8796. UK commercial banks better manage their equity or liquidity than their fixed assets. Management of UK commercial banks seems to be good at managing total income but less so in generating gross interest and rewarding their shareholders through dividends.

Du, Worthingtonb and Zelenyuk (2018)	China	DEA, truncated regression, and double bootstrap.	Total interest expenses, personal expenses, other operating expenses, and non-interest expenses.	Net interest income, net fee commissions, other operating income, and aggregate net income.	Increasing the asset share of other earning assets (securities and derivatives) and decreasing the share of non-earning assets in total assets or increasing total equity is positively associated with bank efficiency.
(Boubaker et. al (2020)	US	Fuzzy multi-objective two-stage DEA,	Bank interest expense, bank non-interest expense, and bank deposit.	Bank interest income, bank non-interest income, and bank lending	Banks affiliated with multi-bank holding companies are more efficient than those affiliated with single-bank holding companies. Banks with powerful CEOs exhibit lower efficiency than others. An inverted U-shaped relationship exists between multi-bank holding company structure and bank efficiency.
Le et al. (2021)	80 Countries	Two stages: Data and GMM.	The ratio of total bank deposits to GDP and the ratio of total bank overhead costs to total assets.	The private credit to GDP as a share of GDP and the ratio of net interest revenue to interest-bearing assets	The first stage shows that the average efficiency scores of these banking systems are relatively low. The second stage indicates a negative relationship between banking efficiency and fintech credit, while more significant fintech credit can promote banking efficiency.
Osei-Tutu and Weill (2022)	76 Countries	Stochastic Frontier Approach (SFA).	Three input prices: The price of funds, the price of labour, and the price of physical capital.	Total loans and investment assets.	Greater bank efficiency improves access to credit for firms. The beneficial impact of bank efficiency to alleviate credit constraints occurs through the demand channel by reducing borrower discouragement to apply for a loan. A positive impact of bank efficiency on credit access is observed for firms of all sizes.

Note: DEA: Data Envelopment Analysis model; BPNN: Back Propagation Neural model; SBM: Slacks-Based Measure model; SFA: Stochastic Frontier Approach. Sources: Author's findings after revising the existing literature on bank efficiency.

To conclude this section, it is worth saying that most single-country-focused studies on the UK banks using static DEA analyses (Drake 2001; Webb 2003; Webb, Bryce and Watson 2010; Tanna, Pasiouras and Nnadi 2011) focused only on the few largest commercial banks in the UK. Concerning the previous studies, this research assesses the UK commercial banks by utilising a unique dataset of 38 UK commercial banks. The sample of this research includes large, small, publicly quoted, privately owned, domestic, and foreign banks. This diversification in the sample helps to i) compare the UK commercial banks in terms of bank size, ownership structure, and ownership status, and ii) the results of this research, unlike the previous studies in UK banks, can be more generalise and benefit all the commercial banks' management, investors, and policymaker. Also, it is worth pointing out that this research uses data covering the period of 2010-2021, reflecting the impact of important recent events such as Brexit and the Covid-19 pandemic.

Regarding the analysis models, unlike Ouenniche and Carrales (2018), whose applied DEA-based analysis framework with a regression-based feedback mechanism to investigate the efficiency of the UK banks, this research differs from the previous work as follows. Firstly, it employs a two-stage non-parametric method, using the Simar and Wilson (2007) DEA bootstrap procedure to estimate efficiency. In the first stage, DEA will be used to estimate the research sample's relative efficiency scores using constant returns to scale (CCR) (Charnes, Cooper and Rhodes 1978) and variable returns to scale (BCC) (Banker, Charnes, and Cooper, 1984). In the second stage, GMM methods will estimate factors affecting bootstrap efficiency scores. According to Du, Worthington and Zelenyuk (2018), this approach obtains more reliable evidence than previous studies analysing bank efficiency. More details on the inputs and outputs, the variables for the second stage of the regression analysis, and the models for estimations will be presented in Chapter 7.

6.5 Summary

This chapter presented the existing literature on bank efficiency and its determinants. The chapter introduces the concept of efficiency and its drivers to give the reader a better understanding before moving to the rest of the chapter. It explains the efficiency types, including scale efficiency, X-efficiency, technical efficiency, and allocative efficiency, and other types, such as pure technical efficiency, cost efficiency, and scope efficiency. Then, the chapter comprehensively explained the Measures of Banking Efficiency. In the first part of Section 6.3, the structural and non-structural measures are explained. The non-structural approach compares performance among banks using different financial ratios. It aims to evidence agency problems in correlations with performance ratios and variables characterising the quality of banks' governance. It also considers the relationship between performance on one side and investment strategies and governance characteristics on the other side.

The structural approach brought a disagreement about the exact banks' output. It has three common sup-approaches: the asset, user cost, and value-added approaches. The second part of Section 6.3 presents the Traditional, Parametric, and Non-Parametric Measures. The traditional method of measuring efficiency uses ratio analysis from several financial institutions. According to this method, financial statements are the primary source of accounting information used to measure a financial institution's operating efficiency.

The parametric method, known as "parametric programming", is generally concerned with the production or expense function base. It is used to estimate the characteristics of the function and measure economies of scale with the assumption that all decision-making units (DMUs) operate efficiently. It can be classified into three different categories: The Stochastic Frontier Approach (SFA), The Thick Frontier Approach (TFA), and The Distribution-Free Approach (DFA). The non-parametric method is also known as the "non-parametric programming approach". The Data Envelopment Approach (DEA) is the most common non-parametric efficiency measure.

Lastly, the chapter discussed the existing literature on bank efficiency by addressing the studies conducted on this topic. It showed the regions, data samples, models for analysis, input and output variables, and the results of these studies in detail. Also, a summary of some recent studies on bank efficiency is presented in Table 6.1

Chapter 7: Methodology and Research Method on Bank Efficiency

7.1 Introduction

Efficiency has always been and will continue to be critical as the world suffers from limited resources; hence, efficiency becomes essential in competition situations. The importance of efficiency becomes apparent in times of crisis and unexpected circumstances (Stewart, Matousek and Nguyen 2016). Removing barriers to market entry extends the way for businesses that work efficiently, resulting in access to cheaper products and services by societies. This encourages businesses in the economy to learn to work efficiently and to be less wasteful in their use of inputs to survive the melting of profit margins created by adverse changes in competition or environmental factors (Barth et al. 2013). For similar reasons, effective and efficient operations are also crucial for the financial and banking sectors, where their efficient functioning is essential for the economies. Unlike other economic sectors, the banking sector takes the function of financial intermediation, which determines resource distribution; hence, the sector has a leading role in the economic development of countries. Therefore, efficiency criteria should be studied for a banking sector performance analysis.

The main objective of this chapter is to describe and explain the methodology and research methods for investigating the efficiency and its determinants of UK banks over the period 2010-2021. The chapter explains how this research will be undertaken and how the data collected will be analysed.

The remainder of the chapter is organised as follows: Section 7.2 presents the research questions. Section 7.3 presents the research philosophy and approach. Section 7.4 presents the research methodology, and a summary of the whole chapter is presented in Section 7.5.

7.2 Research questions

This research investigates bank efficiency in the context of the UK. The purpose of this research is threefold. First, to analyse the bank efficiency of the UK banking sector by applying the advanced semiparametric two-stage method introduced by Simar and Wilson (2007). Second, to provide a detailed analysis of bank efficiency for different banks' sizes, ownership structures, and ownership statuses. Third, to identify the determinants of UK bank efficiency. To this end, this research attempts to answer the following questions:

i. What is the overall efficiency level of the UK commercial banks?
ii. To what extent do the UK commercial banks' characteristics (Size, ownership structure, and ownership status) affect their efficiency?
iii. What are the bank-specific, industry-specific, and macroeconomic determinants of the UK commercial banks' efficiency from 2010 to 2021?

iv. What are the bank-specific, industry-specific, and macroeconomic determinants of the UK commercial banks' efficiency before and after Brexit?

7.3 Research philosophy and approach

Based on its characteristics, aims, and objectives, and in line with the investigation of the UK commercial banks' profitability, this research adopts positivism as a philosophical position to investigate the relationship between the UK banks' efficiency and the internal (bank-specific) and external (industry-specific and macroeconomic) factors. From a philosophical stance and a methodological approach, a deductive approach is used to answer the research questions. A quantitative method is applied as this research uses secondary data, recognised as the most proper for testing the research hypotheses.

7.4 Research Methodology

As mentioned above, this research applies Simar and Wilson's (2007) two-stage procedure to estimate the efficiency of the UK banking sector. In the first stage, the DEA is adopted to estimate the sample's relative efficiency scores using Constant Returns to Scale CRS (CCR model) and Variable Returns to Scale VRS (BCC model). In the second data analysis stage, the Simar and Wilson (2007) procedure will be applied to bootstrap the DEA scores with a bootstrapped regression. In this stage, the research uses the bias-corrected Algorithm 2 as it is preferred and used for inference (Simar and Wilson, 2007). Algorithm 2 is presented in Appendix A.

7.4.1 CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) Models

The most significant DEA models are the CCR (Charnes, Cooper, and Rhodes) and the BCC (Banker, Charnes, and Cooper) models. The CCR was introduced by Charnes, Cooper and Rhodes (1978) to evaluate efficiency and recognize the inefficiency's source and level. Banker, Charnes and Cooper (1984) introduced the BCC model based on the CCR model to estimate the technical efficiency based on the scale of operation in the unit required to render services to beneficiaries at the time of measurement. They assume that there is an association between efficiency and specific operation size. Formulations and descriptions of the CCR and BCC models are presented in Table 7.1.

These models will provide each DMU's CCR and BCC efficiency scores (the overall and pure technical efficiency scores). Under Constant Return to Scale (CRS), it is assumed that outputs vary in direct proportion to the input variance, no matter the DMU size. The CRS may prove unsuitable for a group of DMUs with a large scale of operations. The Variable Return to Scale (VRS) presupposes that modifying inputs fails to produce any proportional output change, meaning that when a DMU is enlarged, its average cost falls or rises.

Table 7.1: The CCR and BCC models.

Formulation	Description
Objective function	
$\boldsymbol{\theta_k}$	θ_k is to be minimised or maximised depending on whether the analysis is input-oriented or output-oriented.
Constraints	
$\sum_{j=1}^{n} \boldsymbol{\lambda_j xi, j} \leq \boldsymbol{\theta_k . xi, k,} \ \ \boldsymbol{i = 1, \ldots, m}$ *OR* $\sum_{j=1}^{n} \boldsymbol{\lambda_j xi, j} \leq \boldsymbol{xi, k,} \ \ \boldsymbol{i = 1, \ldots, m}$	For each input i (i = 1..., m), the amount used by DMU_k's "ideal" benchmark, i.e., its projection on the efficiency frontier, should at most be equal to the amount used by DMU_k adjusted for the degree of technical efficiency of DMU_k or not, depending on whether the analysis is input-oriented or not.
$\sum_{j=1}^{n} \boldsymbol{\lambda_j yi, j} \leq \boldsymbol{\theta_k . yi, k,} \ \ \boldsymbol{i = 1, \ldots, s}$ *OR* $\sum_{j=1}^{n} \boldsymbol{\lambda_j yi, j} \leq \boldsymbol{yi, k,} \ \ \boldsymbol{i = 1, \ldots, s}$	For each output r (r =1..., s), the amount produced by DMU_k 's "ideal" benchmark, i.e., its projection on the efficiency frontier, should be at least as large as the amount produced by DMU_k adjusted for the degree of technical efficiency of DMU_k or not, depending on whether the analysis is output-oriented or not.
$\sum_{j=1}^{n} \boldsymbol{\lambda_j = 1}$	The technology is required to be convex in BCC models. This constraint is relaxed in CCR models.
λ j ≥ 0, j = 1, . . ., *n* $\boldsymbol{\theta_k}$ unrestricted	Other requirements include non-negativity.

Note: X_{ij} : The observed amount of input from the j^{th} type of DMU (X_i, > 0, i = 1, 2..., m, j = 1, 2..., n). Y_{rj} : The observed amount of input from the j^{th} type of DMU (Y_r, > 0, r = 1, 2…m, j = 1, 2, n). U_r: The weight that determines output. V_i: The weight that determines input. r: indicates s different outputs. i: denotes m different inputs. j: indicates n different DMUs. Source: Ouenniche and Carrales (2018).

VRS encompasses the data more closely than CRS and estimates technical efficiency scores greater than or equal to CRS. The VRS has proven to be more popular recently and gives an enhanced reflection of the authentic observations found in the real world. According to Alrafadi, Yusuf and Kamaruddin (2016), the VRS approach is more appropriate than CRS when the sample consists of small to large banks. Another preference for the VRS approach over the CRS is that the more developed the banking system is, the more likely the banks face non-constant returns to scale. Furthermore, the VRS allows banks to deviate from the CRS line (viewed as optimal scale operation) due to some factors such as imperfect competition, regulatory requirements, credit and Loan restrictions, and macroeconomic effects. The CRS is only appropriate when all DMUs operate at an optimal scale. However, if imperfect competition exists, a DMU may not function at an optimal scale.

For a detailed and comprehensive comparison between bank groups, the efficiency scores (CCR and BCC) as an output of the first stage will be investigated using the banks' asset size (small and medium banks, and large and exceptionally large banks), bank ownership structure (publicly quoted banks and privately-owned banks), and bank ownership status (domestic banks and foreign banks). This step is taken to present comparable results amongst the different banking groups, producing more straightforward and understandable findings. The research uses an extensive panel data set to analyse efficiency in the UK banking sector for the first time using a data set that includes 50 UK banks from 2010 to 2021.

7.4.2 Bootstrap two-stage procedure

The first data analysis stage will estimate banks' technical efficiency, using the DEA to demonstrate which bank is the most efficient. Banks are ranked based on their productivity in the period 2010- 2021. In the second stage, the Simar and Wilson (2007) procedure will bootstrap the DEA scores with a truncated bootstrapped regression (Stewart, Matousek and Nguyen 2016; Wijesiri, Viganò and Meoli 2015).

7.4.2.1 First-stage DEA efficiency estimate

Assuming the j^{th} bank with outputs and inputs of Y_{rj}, X_{ij} (are all positive), where U_r and V_i the variable weights are determined by solving the problem below (Charnes, Cooper and Rhodes 1978).

$$\text{Max } \hat{\delta}_0 = \frac{\sum_{r=1}^{s} U_r\, Y_{r,0}}{\sum_{i=1}^{m} V_i\, X_{i,0}} \qquad \text{Eq. (7.1)}$$

Subject to:

$$\frac{\sum_{r=1}^{s} U_r\, Y_{r,0}}{\sum_{i=1}^{m} V_i\, X_{i,0}} \leq 1;\ j = 1, \ldots, n \qquad \text{Eq. (7.2)}$$

$U_r, V_i \geq 0;\ r = 1, 2, \ldots, s;\ i = 1, 2 \ldots, m$

Where $\hat{\delta}_0$ presents the efficiency of DMU to be estimated, U_r and V_i are weights to be optimized. $Y_{r,j}$ presents the observed amount of output of the r^{th} type for the j^{th} DMU. $X_{i,j}$ presents the observed amount of input from the i^{th} type for the j^{th} DMU. r indicates the s different outputs. i denotes the m different inputs, and j indicates the n different DMUs.

According to Stewart, Matousek, and Nguyen (2016), the actual efficiency scores, $\hat{\delta}_0$, are not observed directly. Instead, they are empirically estimated. The two-stage approach has been used in studies where efficiencies are estimated in the first stage. Then, the estimated efficiency or ratios of estimated efficiencies and Malmquist indices are regressed on covariates that are viewed as environmental variables and are typically different from those used in the first stage (Simar and Wilson 2007; Wijesiri, Viganò, and Meoli 2015).

Simar and Wilson (2007) criticised this two-stage method as the DEA efficiency estimates are biased and serially associated, thus invalidating the conventional inferences in the second stage. They proposed a technique based on a double bootstrap, which provides a confidence interval for the efficiency estimates and results in consistent inferences for variables explaining efficiency.

7.4.2.2 Second-stage regression

A data-generating process is assumed to generate the original data to implement the bootstrap procedure for DEA. Then, this process will be simulated using a new (pseudo) data set drawn from the original data set (Step: 3.3 in Algorithm 2, see Appendix A). The DEA model will be re-estimated with this new data (Steps 4 and 5 in Algorithm 2, see Appendix A). This process will be repeated two thousand times (Step: 6 in Algorithm 2, see Appendix A). This number of bootstrap replications will be used to create estimated confidence intervals in the algorithm. The confidence-interval estimation is equivalent to estimating distributions' tails, which demands more information. According to Simar and Wilson (2007), the step of the 2,000 replications is preferred over one thousand as more accurate estimates can be achieved with more significant replications. Nevertheless, the calculation time also rises when the number of replications increases. When this step is done, an empirical distribution of these bootstrap values can be driven (Wijesiri, Viganò, and Meoli 2015).

The efficiency scores $\widehat{(\delta_{i,t}})$ of banks obtained in the first stage will result in inconsistent and biased estimates if regressed on explanatory variables in the second stage. In their studies with Monte Carlo experiments, Simar and Wilson (2007) demonstrate that explanatory variables are correlated with the error term as input and output variables are correlated with explanatory variables. Moreover, they point out that DEA efficiency estimates are serially interconnected and yield inconsistent and biased estimates in the second stage. To overcome this issue, they recommended that one hundred replications are sufficient to compute the bias-corrected estimates $(\hat{\hat{\delta}}_{i,t})$, which requires only the computation of a mean and then a difference. This research will follow this recommendation, and one hundred bootstrap replications will be used to compute the bias-corrected efficiency scores $\hat{\hat{\delta}}_{i,t}$ (Step 3, as shown in Algorithm 2, Appendix A). Then, the bias-corrected efficiency scores $\hat{\hat{\delta}}_{i,t}$ yielded in the first stage of the analysis will be regressed on a set of explanatory variables (bank-specific, industry-specific, and macroeconomic variables) to determine the factors explaining bank efficiencies using the following regression specification:

$$\hat{\hat{\delta}}_{i,t} = \beta z_i + \varepsilon_i \qquad \text{Eq. (7.3)}$$

Or equivalently:

$$\hat{\hat{\delta}}_{i,t} = \mu + \sum_{j=1}^{J} \beta_j X_{it}^{j} + \sum_{l=1}^{L} \beta_l X_{it}^{l} + \sum_{m=1}^{M} \beta_m X_{it}^{m} + \varepsilon_{it}, \text{ where } \varepsilon_{it} = v_i + u_{it} \qquad \text{Eq. (7.4)}$$

Where $\hat{\hat{\delta}}_{i,t}$ represents the efficiency score, estimated in stage 1, of bank *i* at time *t*, with *i* = 1, ..., *N*, *t* = 1, ..., T, β_0 is a constant term, X_{it}'s are the explanatory variables and ε_{it} the disturbance, with v_i the unobserved bank-specific effect and u_{it} the idiosyncratic error. The X_{it}'s are grouped into bank-specific X_{it}^{j}, industry-specific X_{it}^{l}, and macroeconomic variables X_{it}^{m} .

The percentile bootstrap confidence intervals of the coefficients that will be estimated in the second stage regression will be constructed as follows:

$$\text{Prob } (Lower_{\alpha,j} \leq \beta_j \leq Upper_{\alpha,j}) = 1 - \alpha \qquad \text{Eq. (7.5)}$$

Where α presents small values indicating the probability of a Type I error (for example, α = 0.05 for a 5% significance level) and 0 < α < 1. $Lower_{\alpha,j}$ and $Upper_{\alpha,j}$ are estimated using the empirical intervals obtained from the bootstrap values thus:

$$Prob\ (-\hat{b}_\alpha \leq \hat{\hat{\beta}}_j^* - \hat{\hat{\beta}}_j \leq -\hat{a}_\alpha) \approx 1-\alpha$$

Where: $Upper_{\alpha,j} = \hat{\hat{\beta}}_j + \hat{a}_\alpha$ and $Lower_{\alpha,j} = \hat{\hat{\beta}}_j + \hat{b}_\alpha$

Given the dynamic nature of the bank performance (Athanasoglou, Brissimis, and Delis (2008), this research uses a methodology based on a dynamic panel model to investigate the impact of environmental covariates (bank-specific, industry-specific, and macroeconomic variables) on the UK banks' efficiency.

The pooled OLS and FE methods produce biased, inconsistent estimations as N tends to infinity (if they are consistent for large T). Hence, using dynamic panel techniques can deal with the biases and inconsistencies of estimates. Another issue with bank efficiency's estimating models is the possible endogeneity of regressors. The Generalised Method of Moments (GMM) estimator accounts for endogeneity by instrumenting the lagged values of the dependent variable and any other potentially endogenous regressors using equations in levels and differences. In contrast, all regressors will be lagged, except those undoubtedly exogenous. Another critical problem is unobservable heterogeneity across banks and differences in corporate governance, which cannot be sufficiently measured. The system GMM estimator controls for unobserved heterogeneity in addition to instrumenting lags of the dependent variable and other potentially endogenous regressors to yield consistently estimated parameters (Stewart, Matousek, and Nguyen, 2016).

A model specification is needed when a lagged dependent variable is comprised among the regressors. Equation (7.4) is developed with the lagged efficiency as follows.

$$\hat{\hat{\delta}}_{i,t} = \mu + \alpha\hat{\hat{\delta}}_{i,t-1} + \sum_{j=1}^{J} \beta_j X_{it-1}^{j} + \sum_{l=1}^{L} \beta_l X_{it}^{l} + \sum_{m=1}^{M} \beta_m X_{it}^{m} + \varepsilon_{it} \qquad \text{Eq. (7.8)}$$

Where $\hat{\hat{\delta}}_{i,t-1}$ is the one-period lagged efficiency and presents the bias-corrected efficiency scores (biased corrected constant return to scale (CCR-BC) and variable return to scale (BCC-BC)) as our primary measure of bank efficiency (Wanke, Barros and Emrouznejad, 2016 and Du, Worthington and Zelenyuk, 2018). α is the speed of adjustment to equilibrium. Values of α between 0 and 1 indicate that efficiency persists, but they will return to their average level. If the value of α is close to 0, it tells that the industry is relatively competitive, while if the value is close to 1, it implies a less competitive structure (Athanasoglou, Brissimis, and Delis, 2008). X_{it-1}^{j} are the bank-specific variables lagged by one period.

The primary standard estimator used for the second analysis stage (regression analysis) is the Generalised Method of Moments (GMM). For comparison purposes, the results of the Ordinary Least Square (OLS) and the Fixed Effects (FE) approaches will be presented in the following Chapter 8. More explanation and comparison between the three estimators are given in Chapter 4, Section 4.8.2.

7.4.3 Specification of the inputs and outputs (First stage)

Concerning the type of efficiency assessment perspective that drives the choices of inputs and outputs, there is no simple solution to the problem of input and output specification. Reasonable arguments can be made for all approaches. According to Matthews and Thompson (2014), there are two main approaches to financial institutions' input and output specification: the production and the intermediation methods.

The production approach views the bank as a producer, just like a business in the production market. Inputs are physical entities such as labour and physical capital. From this approach's perspective, the bank produces accounts of sizes by processing deposits and loans, incurring capital and labour costs. The promoters of this approach argue that inputs are measured as operating costs. At the same time, all deposits should be treated as an output since they are associated with liquidity and safekeeping and generate value added. Other outputs are net interest and non-interest income from the profit and loss account.

The intermediation approach views the bank as an intermediary where its output is measured by the value of loans and investments together with off-balance-sheet income, and its input costs are measured by the payments made to factors of production, including interest payments. According to this approach, deposits may be treated as inputs or outputs. From the bank managers' perspective, deposits are input as obtaining profits by purchasing earning assets such as loans and investments is essential. Contrarily, deposits are output from the customer's point of view since they create value for the customer through payment, record-keeping, and security facilities. Alternatively, the intermediation approach may concentrate on income (net interest and non-interest income) being characterised as output and the related expenses as input.

Table 7.2: Definition of selected input and output variables.

Specification	Variables	Descriptions
Inputs		
	Customer deposits	Present the total deposits from corporate and private customers.
	Personnel expenses	A measure of labour that presents all components related to employees and their respective payments.
	Interest expenses	Present the total expenses, not including personnel expenses.
	Total fixed Assets	Present the total value of the long-term tangible property or equipment that the banks own and use in operations to generate income.
Outputs		
	Securities	Present the investments and trading securities of the bank.
	Gross Loans	Present the bank's total loans for the corporate and private sectors and all other loans.
	Net Interest Income	Present the difference between the revenue generated from interest-bearing assets and the expenses associated with paying on the interest-bearing liabilities.

Note: Values of inputs and outputs will be gathered from banks' financial statements (balance sheet and income statement). Thus, the input and output variables selection are based on the available data for the 38 UK commercial banks included in this research and their ability to provide financial services.

The existing literature on bank efficiency shows that both approaches have been applied differently depending on the data availability and the research's purpose. This research assumes that the UK banking sector is the transformer of deposits and purchased funds into customer loans and other loans. Accordingly, this research applies the intermediation approach. This choice is also due to data availability for inputs and outputs. All the data are indices of bank *i* in year *t*. As shown in Table 7.2, inputs used in this research are customer deposits, personnel expenses, interest expenses, and total fixed assets, while outputs include securities, gross loans, and net interest income. A summary statistic of these inputs and outputs, including the mean, median, standard deviation, minimum value, and maximum value, will be presented in Chapter 8.

7.4.4 Specification of variables (Second stage)

7.4.4.1 Dependent variables

The second stage of the analysis aims to investigate the factors that affect bank efficiency: overall technical efficiency (CCR) and pure technical efficiency (BCC). Following the authors (Stewart, Matousek, and Nguyen 2016; Wanke, Barros, and Emrouznejad 2016; Du, Worthington, and Zelenyuk 2018), this research uses the biased corrected constant return to scale (CCR-BC) and variable return to scale (BCC-BC), which will be generated from first-stage analysis, as the primary measures of bank efficiency.

7.4.4.2 Independent variables

This research will employ the same independent variables used to investigate the bank's profitability with two additional profitability measures, ROA and NIM. However, the predictive values of ROA and NIM from previous profitability models will be used to solve the endogeneity issue.

The sixteen explanatory variables (PVROA, PVNIM, SIZE, FGR, LCR, NSFR, NPL, LOANGR, LOAN, DEP, MC, DB, PC, INF, GDPGR, and COV) will be used in the second stage of data analysis to determine the factors explaining bank efficiency (CCR-BC and BCC-BC). These variables include bank-specific, industry-specific, and macroeconomic variables. To avoid repeating the content regarding these independent variables, see Chapter 4, Section 4.6.2.1. A summary of the dependent and independent variables, their descriptions, and the expected effect on banks' efficiency is presented in Table 7.3.

Table 7.3: Variables used, descriptions, and their expected effect on banks' efficiency.

Variables	Abv	Description	Measures	Expected Signs
Dependent Variables				
	CCR-BC	Overall technical efficiency	The constant return to scale bias-corrected.	
	BCC-BC	Pure technical efficiency	The variable return to scale bias-corrected.	
Independent Variables				
	PVROA	Predicted value of return on assets	Predicted value of (net profit / total assets) used in profitability models.	-/+
	PVNIM	Predicted value of net interest margin	Predicted value of (net interest income / average earning assets) used in profitability models.	+/-
	SIZE	Bank size	Bank's natural logarithm total assets (£m).	-/+
	NPL	Non-performing loan ratio	Bank's total value of non-performing loans by its total value of outstanding loans.	-
	LCR	Liquidity coverage ratio	Bank's stock of high-quality liquid assets divided by Total net cash outflows over the next 30 days.	-
	NSFR	Net stable funding ratio	The bank's available stable funding (ASF) is divided by its required stable funding.	+
	FGR	Financing gap ratio	Net loans minus total deposits divided by total assets.	+
	LOAN	Loan specialisation ratio	Net loans are divided by total assets.	+
	LOANGR	Laon Growth Ratio	The growth in the bank's gross loan as a per centage.	-
	DEP	Deposits ratio	Customer deposits are divided by total assets.	+
	PC	Ownership structure	Dummy variable equals1 for publicly-quoted banks and 0 otherwise.	+
	DB	Ownership status	Dummy variable equals1 for domestic banks and 0 otherwise.	+
	MC	Market concentration	The sum of the market share for the most significant UK four banks.	-
	INF	Inflation rate	UK Inflation rate (annual %).	+/-
	GDPGR	GDP growth rate	The growth in GDP of the UK (annual %).	+
	COV	Covid-19	Dummy variable equals 1 for the years of (Covid-19) 2020-2021 and 0 otherwise.	-

7.5 Summary

This chapter presented and explained the methodology for investigating the efficiency and its determinants in the UK banking sector. The chapter is organised into sections presenting the research questions and the research hypothesis. Also, it presented the research philosophy and approach, the data type, and the collection method. Moreover, it presented the research methodology through subsections where the CCR and BCC models, the bootstrap two-stage procedure, the first-stage DEA efficiency estimate, and the second-stage regression were discussed in detail. Then, the chapter provided an explanation of the specification of the inputs and outputs and the specification of the dependent and independent variables that will be used for the data analysis.

This chapter included three primary tables presenting valuable information. Table 7.1 presents The CCR and BCC models. Table 7.2 provides definitions and descriptions of the selected input and output variables used for the first stage of the analysis to generate the efficiency scores. Lastly, Table 7.3 presents the descriptions and the expected effect of the independent variables employed in the second analysis stage. These variables were classified into bank-specific, industry-specific, and macroeconomic factors.

Chapter 8: Results and discussion on bank efficiency

8.1 Introduction

This chapter focuses on empirical data analysis. The investigation is based on an unbalanced panel dataset covering 416 bank-year observations of 38 domestic and foreign commercial banks operating in the UK banking sector from 2010 to 2021. For the first stage analysis, relevant environment-independent inputs and outputs were specified for the DEA analysis within this research method. These inputs and outputs were first performed to compute the relevant efficiency scores for the analysis considering the overall technical efficiency (CCR) and pure technical efficiency (BCC) by solving the proper DEA models. The estimated efficiency scores from this stage have been used as dependent variables for the second data analysis stage. For the second stage, twelve econometric models (one model of OLS and FE and four GMM models for each proxy of efficiency) were used to examine the relationship between the UK banks' efficiency (overall technical efficiency and pure technical efficiency as proxied by RCC-BC and BCC-BC) and the presumed environmental explanatory variables.

The chapter illustrates the econometric results, including the descriptive statistics for both analysis stages, the test for multicollinearity, and regression analysis using the OLS, FE, and GMM models. The chapter is organised as follows. Section 8.2 presents the descriptive statistics of the selected inputs and outputs. Section 8.3 presents the empirical results of DEA efficiency estimation (first stage). Section 8.4, which includes sub-sections, presents the results on determinants of bank efficiency (second stage). It discusses the descriptive statistics for the variables used in the regression analysis, the correlation matrix and the test for multicollinearity, the models and steps used in the estimation process, and the regression analysis results for the whole, pre-Brexit and post-Brexit samples. A summary of the findings is provided in Section 8.5.

8.2 Descriptive statistics of the selected inputs and outputs

Within the method of this research, a set of relevant environment-independent inputs and outputs were specified for the DEA analysis. These inputs and outputs are first performed to compute the relevant efficiency scores for the analysis considering the overall technical efficiency (CCR) and pure technical efficiency (BCC) by solving the proper DEA models. The inputs and outputs for this research were collected from UK banks' financial statements (balance sheets and income statements). These inputs and outputs are environment-independent.

Classifying the inputs and outputs used in the UK commercial banks' financial statements analysis shows that inputs are typically selected based on resources, costs, or financial burden. In contrast, outputs are commonly selected based on the bank's ability to supply financial services (loans and deposits), generate revenue (income and investments), and acquire more assets (investments) (Ouenniche et al. 2017; Ouenniche and Carrales 2018).

Accordingly, this research's selection of inputs and outputs is based on resources and the banks' ability to provide financial services. Customer deposits, personnel expenses (as a measure for labour due to the unavailability of the number of employees for all UK banks), capital as measured by total fixed assets, and costs (total interest expenses not including personnel expense) were used as inputs. The outputs are selected based on the ability of banks to acquire more assets (investments), provide financial services, and generate revenues. Securities (as investment and trading securities of the banks), gross loans (as total loans for the corporate and private sectors and other loans), and net interest income were used as outputs. This selection of inputs and outputs aligns with the intermediation approach, which considers banks transforming deposits and purchased funds into loans and other assets. Inputs are represented as total operating costs plus interest and deposits, while output is estimated in money units.

A snapshot of the UK commercial banks' inputs and outputs used in this research dataset is summarised in Table 8.1. The first column shows the selected variables (inputs and outputs), while other columns report various statistics, including the mean, median, standard deviation, and minimum and maximum values.

Table 8.1: Descriptive statistics of inputs and outputs (Units: £million).

Variables	Mean	Median	Std Deviation	Minimum	Maximum
Inputs					
Customer Deposits	80,663.16	1,891.212	199,641.105	10.978	1,273,317.069
Personnel Expenses	1,185.48	37.669	2,994.931	0.012	14,704.114
Interest Expenses	1,136.29	37.363	2,854.204	0.42	18,468.163
Total Fixed Assets	13,899.53	172.461	77,875.122	0.13	924,605
Outputs					
Securities	37,480.71	548.051	107,210.504	0.5	602,574.883
Gross Loans	71,610.67	1,839.079	164,756.038	0.147	796,764.851
Net Interest Income	1,911.98	66.830	4,702.579	-2.497	26,299.722

Sources: Author’s calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

As for inputs, the statistics in Table 8.1 show that the minimum values of (£10.978m) and (£0.42m) for Customer Deposits and Personnel Expenses were recorded for Oaknorth Bank Plc in 2015, the year of its establishment. However, the bank's annually collected data shows that it recorded a gradual increase in customer deposit values since its establishment to reach a value of (£2,422.751m) in 2021. At the same time, the values of (£0.012m) and (£0.13m) for Personnel Expenses and Total Fixed Assets were recorded for the National Bank of Egypt (UK) Limited in 2021 and 2017, respectively. The statistics also show that all maximum values of inputs for Customer Deposits, Personnel Expenses, Personnel Expenses, and Total Fixed Assets of (£1,273,317.069m) in 2021, (£14,704.114m) in 2016, (£18,468.163m) in 2019 and (£924,605m) in 2021 were recorded for HSBC Holdings Plc, respectively.

As for outputs, Securities, Gross Loans, and Net Interest Income show the minimum values of (£0.5m), (£147,000m), and (£-2.497m) were recorded for Oaknorth Bank Plc in 2016, Metro Bank Plc in 2010 ICBC Standard Bank Plc in 2015, respectively. In contrast, all maximum values of the three outputs with values of (£602,574.883m), (£796,764.851m) and (£26,299,722m) were found for HSBC Holdings Plc in 2020, 2019 and 2011, respectively.

It is worth mentioning that HSBC Holdings Plc is the biggest bank in the UK banking sector in terms of total assets, being £2,201,830.623m in 2021, 22.78% of the banking sector's total assets, followed by (£1,349,814m, £886,525m, and £781,992m), 13.69%, 8.77% and 7.73% for the rest of the big four banks: Barclays Plc, Lloyds Banking Group Plc and NatWest Group Plc, respectively. More information regarding market shares for this research bank sample is given in (Chapter 4, Table 4.1).

8.3 Empirical results of DEA efficiency estimation (first stage)

The inputs and outputs were performed to compute efficiency scores. The estimated efficiency scores from this stage are presented in Table 8.2 and Table 8.3. The yearly technical efficiency average scores $\widehat{\delta_{\imath,t}}$ and $\widehat{\widehat{\delta_{\imath,t}}}$ of the UK banks over the research period of 2010-2021 are shown in Table 8.2, while all banks included in this research by names are presented with their technical efficiency average scores $\widehat{\delta_{\imath,t}}$ and $\widehat{\widehat{\delta_{\imath,t}}}$ in Table 8.3

The top half of Table 8.2 reports scores based on the constant returns to scale (CCR), and the lower half provides efficiency measures using variable returns to scale (BCC). The average initial technical efficiency score $\widehat{\delta_{\imath,t}}$ for the entire system is 0.603, assuming constant returns to scale (CCR) and 0.691, assuming variable returns to scale (BCC). From these initial estimates, Algorithm 2 has been applied to obtain the bias-corrected double bootstrap scores $\widehat{\widehat{\delta_{\imath,t}}}$ (CCR-BC and BCC-BC) using the method of (Simar and Wilson 2007).

The average double bootstrap technical efficiency score $\widehat{\widehat{\delta_{\imath,t}}}$ (CCR-BC and BCC-BC) obtained from (Algorithm 2) for the entire system is 0.459 for the constant returns to scale (CCR) and 0.552 for variable returns to scale (BCC). The results in Table 8.2 show that the efficiency scores are almost stable for the entire system for the period this research covers. The $\widehat{\widehat{\delta_{\imath,t}}}$ show a highest value of 0.476 in 2010 for (CCR) with a slight decrease to 0.456 in 2016, 2019, 2020, and 2021, and 0.562 for (BCC) in 2013, with a decrease to 0.549 in 2021. These results provide evidence that the technical efficiency of UK banks was affected by the events of Brexit and Covid-19, which supports the use of these variables in this research data analysis. As a measure of pure technical efficiency, the BCC score reflects management skills. Its average score of 0.552 is higher than the CCR score of 0.459 to measure overall technical efficiency.

Table 8.2: The entire sample yearly technical efficiency average scores ($\widehat{\delta_{\iota,t}}$) and ($\widehat{\widehat{\delta_{\iota,t}}}$) of the UK from 2010 to 2021.

	$\widehat{\boldsymbol{\delta}_{\iota,t}}$	$\widehat{\widehat{\boldsymbol{\delta}_{\iota,t}}}$	Algorithm 2, $\widehat{\widehat{\boldsymbol{\delta}_{\iota,t}}}$ Confidence Interval: Lower bound	Algorithm 2, $\widehat{\widehat{\boldsymbol{\delta}_{\iota,t}}}$ Confidence Interval: Upper bound	No. Banks	No. Efficient banks: $\widehat{\delta_{\iota,t}}$	No. Efficient banks: $\widehat{\widehat{\delta_{\iota,t}}}$
CCR							
2010	0.623	0.476	0.487	0.605	27	1	0
2011	0.600	0.457	0.469	0.582	30	1	0
2012	0.600	0.457	0.469	0.582	30	3	0
2013	0.608	0.462	0.474	0.589	34	3	0
2014	0.605	0.461	0.473	0.587	36	4	0
2015	0.601	0.457	0.469	0.583	38	2	0
2016	0.597	0.456	0.468	0.580	38	4	0
2017	0.601	0.457	0.469	0.583	38	4	0
2018	0.601	0.457	0.469	0.583	38	5	0
2019	0.600	0.456	0.469	0.582	38	2	0
2020	0.600	0.456	0.469	0.582	38	4	0
2021	0.600	0.456	0.468	0.582	38	9	0
Mean	**0.603**	**0.459**	**0.471**	**0.585**			
BCC							
2010	0.654	0.520	0.522	0.644	27	7	0
2011	0.698	0.557	0.553	0.688	30	4	0
2012	0.697	0.556	0.552	0.687	30	4	0
2013	0.704	0.562	0.557	0.694	34	5	0
2014	0.701	0.560	0.554	0.691	36	9	0
2015	0.695	0.555	0.551	0.685	38	3	0
2016	0.695	0.555	0.551	0.685	38	5	0
2017	0.693	0.553	0.549	0.683	38	7	0
2018	0.692	0.552	0.548	0.682	38	8	0
2019	0.690	0.551	0.547	0.680	38	3	0
2020	0.689	0.550	0.546	0.679	38	7	0
2021	0.687	0.549	0.546	0.677	38	13	0
Mean	**0.691**	**0.552**	**0.548**	**0.681**			

Sources: Author's calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

The column headed (No. Efficient banks) in Table 8.2 shows that $\widehat{\delta_{\iota,t}}$ (CCR and BCC) measures indicate that only one bank (ICBC Standard Bank Plc) for the CCR measure and seven banks, including the big four banks (HSBC Holdings Plc, Barclays Plc, Lloyds Banking Group Plc, NatWest Group Plc) and other banks (Santander UK Plc, Credit Suisse International, ICBC Standard Bank Plc) for the BCC out of a total of 27 banks were on the efficient frontier in 2010. According to the CCR (BCC) efficiency measures, 9 (13) out of 38 UK commercial banks were on the efficient frontier in 2021. The column also shows that the number of efficient banks fluctuated over the research period.

Although the $\widehat{\widehat{\delta_{\iota,t}}}$ (CCR-BC and BCC-BC) efficiency scores show differences in their patterns, a clear positive correlation exists between them, as presented in Figure 8.1 and Figure 8.2. The CCR-BC and BCC-BC measures have been used independently as dependent variables in the second data analysis stage. Using these two ratios enables the estimation of scale efficiency that reflects both managerial skills and scale effect.

Figure 8.1: A scatter plot of $\widehat{\widehat{\delta_{\iota,t}}}$ (CCR and BCC) efficiency scores.

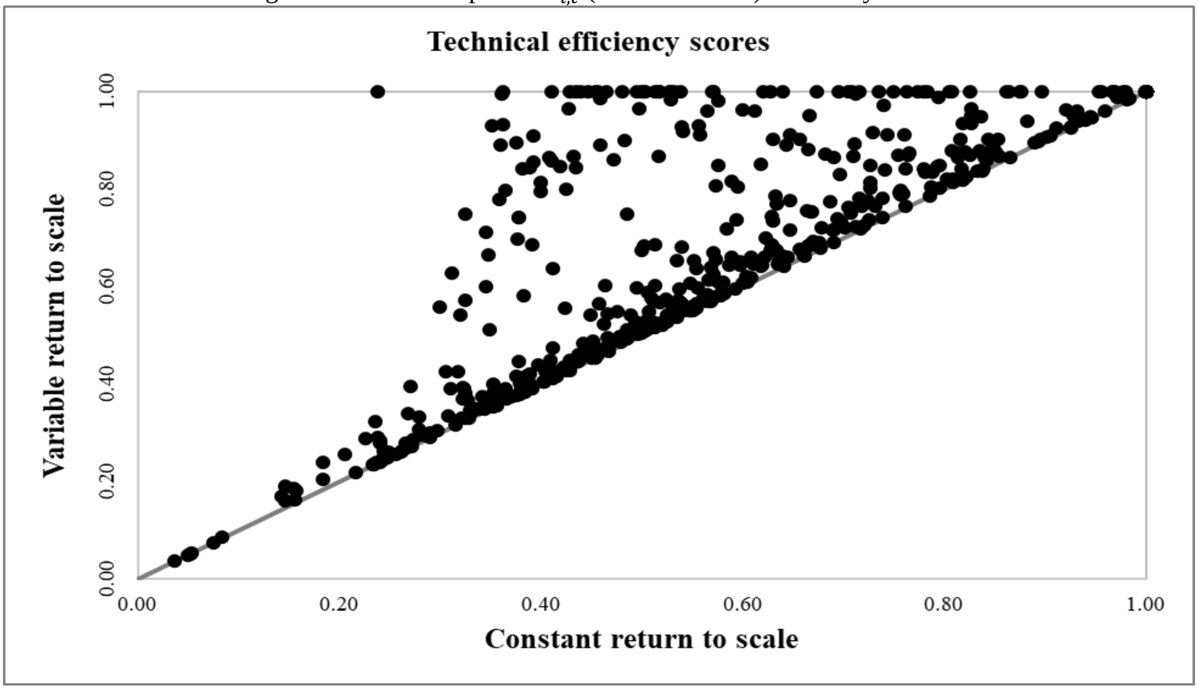


Figure 8.2: A scatter plot of $\widehat{\widehat{\delta_{\iota,t}}}$ (CCR-BC and BCC-BC) efficiency scores.

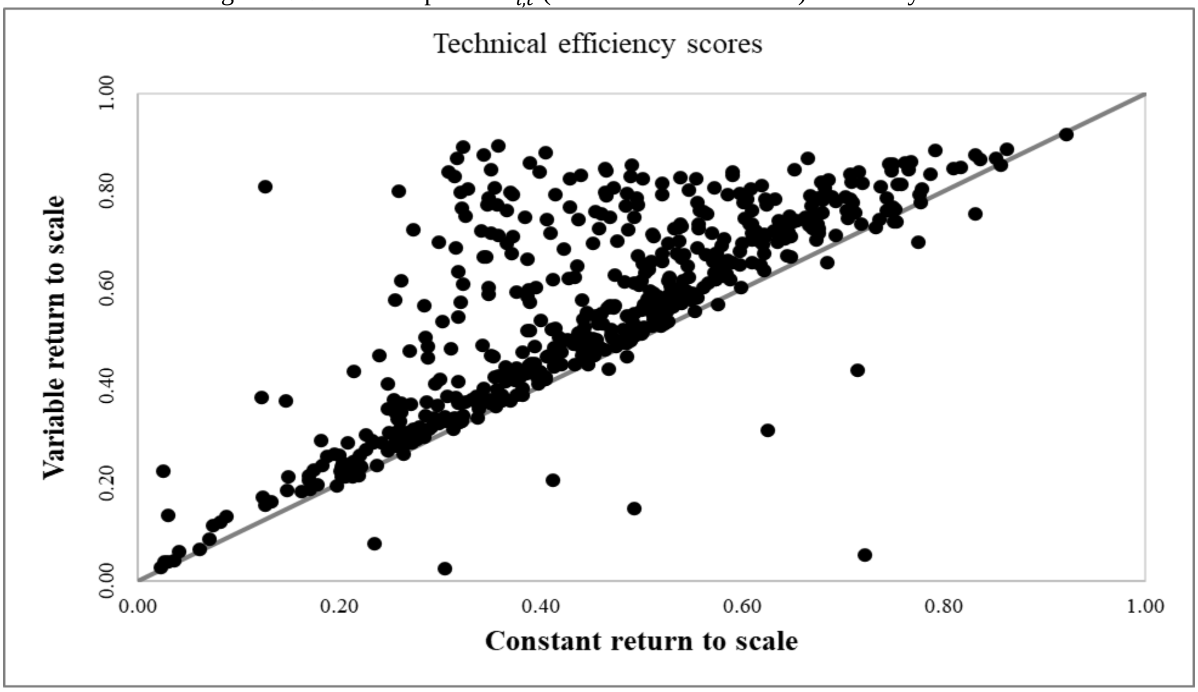


Table 8.3: Average scores for the technical efficiency of the double bootstrap method ($\widehat{\widehat{\delta_{\iota,t}}}$) of the UK commercial banks from 2010 to 2021.

ID	Bank	Obs./ Bank	$\widehat{\widehat{\delta_{\iota,t}}}$ (CCR-BC)	$\widehat{\widehat{\delta_{\iota,t}}}$ (BCC-BC)
1	HSBC Holdings Plc	12	0.46	0.77
2	Barclays Plc	12	0.34	0.76
3	Lloyds Banking Group Plc	12	0.49	0.77
4	NatWest Group Plc	12	0.42	0.78
5	Standard Chartered Plc	12	0.32	0.63
6	Santander UK Plc	12	0.52	0.75
7	Virgin Money UK Plc	7	0.54	0.77
8	SMBC Bank International Plc	12	0.29	0.35
9	Bank of Ireland (UK) Plc	11	0.57	0.73
10	The Co-Operative Bank	12	0.42	0.49
11	Metro Bank Plc	12	0.32	0.33
12	Scotiabank Europe Plc	11	0.38	0.56
13	ICBC Standard Bank Plc	12	0.35	0.46
14	AIB Group (UK) Plc	12	0.42	0.51
15	Aldermore Bank Plc	12	0.63	0.56
16	Close Brothers Group Plc	12	0.66	0.74
17	Paragon Bank Plc	8	0.49	0.59
18	Bank Of New York Mellon Ltd (The)	12	0.07	0.13
19	Shawbrook Bank Limited	11	0.50	0.59
20	Sainsbury's Bank Plc	12	0.57	0.65
21	British Arab Commercial Bank Plc	12	0.39	0.43
22	ICICI Bank UK Plc	12	0.48	0.55
23	Secure Trust Bank	12	0.76	0.72
24	Bank Leumi (UK) Plc	12	0.46	0.48
25	Bank of China (UK) Ltd	12	0.32	0.36
26	United Trust Bank Limited	9	0.51	0.42
27	FBN Bank (UK) Limited	12	0.60	0.66
28	Europe Arab Bank Plc	12	0.37	0.40
29	Unity Trust Bank Plc	9	0.51	0.42
30	Hampshire Trust Bank Plc	7	0.51	0.56
31	National Bank of Kuwait (International)	8	0.49	0.52
23	The Access Bank UK Limited	9	0.46	0.50
33	Oaknorth Bank Plc	7	0.47	0.56
34	ABC International Bank Plc	12	0.36	0.44
35	National Bank of Egypt (UK) Limited	9	0.49	0.40
36	C Hoare & Co	12	0.56	0.61
37	ICBC (London) Plc	12	0.49	0.53
38	Julian Hodge Bank Limited	12	0.43	0.48
		Mean	**0.45**	**0.55**

Sources: Author’s calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

Table 8.3 presents the efficiency scores of each bank of the 38 UK commercial banks averaged from 2010 to 2021, assuming constant and variable returns to scale. While the banks mentioned above, among others, are efficient in specific years, the average scores $\widehat{\widehat{\delta_{\iota,t}}}$ (CCR-BC and BCC-BC) over the entire period, all banks are inefficient or have experienced periods of relative inefficiency). As mentioned earlier and presented in Table 8.2, during 2016-2021 (the period of Brexit and Covid-19), overall average banks' efficiency scores slightly fell for both constant and variable returns to scale. Results in Table 8.3 show that UK commercial banks have a mean of 0.55 for the average scores (BCC-BC) compared to 0.45 for the (CCR-BC). This finding indicates that UK commercial banks are more efficient regarding pure technical efficiency than overall technical efficiency. The higher average scores

(BCC-BC) are found for banks holding more than (£50bn) in total assets. The highest value found is 0.78 for NatWest Group Plc, followed by 0.77 for HSBC Holdings Plc, Lloyds Banking Group Plc, Virgin Money UK Plc, and 0.76 for Barclays Plc. For the average scores (CCR-BC), most high values are found for banks whose total assets are less (than £50bn). The highest value was 0.76 for Secure Trust Bank, followed by 0.66 and 0.60 for Close Brothers Group Plc and FCE Bank Plc, respectively. The lowest average scores are found for Bank Of New York Mellon Ltd (The), with average scores CCR-BC (BCC-BC) of 0.07 (0.13), indicating the most inefficient bank among the sample.

To stand on the UK banks' overall technical efficiency, banks for the first analysis stage in this research are classified into three groups based on their characteristics (bank size, ownership structure, and ownership status). For comparison purposes between UK commercial banks, Table 8.4, Table 8.5, and Table 8.6 are created based on the estimated efficiency scores presenting the average scores for the initial technical efficiency ($\widehat{\delta_{\imath,t}}$) and the technical efficiency of the double bootstrap method ($\widehat{\widehat{\delta_{\imath,t}}}$) for the UK commercial banks based on size, ownership structure, and ownership status, respectively.

As for size, banks were divided into two main groups based on total assets. Banks with average total assets of more than (£50bn) over the research period (2010-2021) were considered large and exceptionally large ones, while banks with average total assets of less than (£50bn) were considered small and medium banks. This classification ended up with nine large and exceptionally large banks and forty-one small and medium banks. The results in Table 8.4 indicate that small and medium banks are more efficient than large and exceptionally large banks regarding the constant returns to scale as they have a larger average value of ($\widehat{\widehat{\delta_{\imath,t}}}$) CCR-BC being 0.452 compared to a value of 0.421 for large and large banks. In contrast, large and exceptionally large banks have a more significant value of 0.704 for pure technical efficiency than 0.505 for small and medium banks. The results also show that the yearly average efficiency scores ($\widehat{\widehat{\delta_{\imath,t}}}$) CCR-BC of large and very large banks reached the highest value of 0.427 in 2016, the year of Brexit, and then the value gradually decreased to the lowest value of 0.410 in 2020-2021, reflecting the negative impact of Covid-19. Regarding **(**$\widehat{\widehat{\delta_{\imath,t}}}$) BCC-BC, the same scenario occurred where the value decreased from 0.710 in 2010 to 0.697 in 2020 and 2021. As for small and medium banks, the banks maintained almost the same average value of 0.452 during the entire period for CCR-BC. The average (BCC-BC) increased from 0.503 in 2010 to a maximum value of 0.510 in 2015 and 2016, then decreased to the exact value of 2010, the lowest value throughout the research period, being 0.503.

Banks were divided into two main groups for the ownership structure: publicly quoted (10 banks) and privately-owned banks (28 banks). The results in Table 8.5 show that publicly quoted banks maintain a (BCC-BC) of 0.580 for 2010-2021, indicating more efficiency over the privately-owned banks with 0.525 on average for the same period. The privately-owned banks’ average scores for BCC-BC had the highest value of 0.528 in 2011 before decreasing, reaching the lowest value of 0.521 in 2021, reflecting the impact of Covid-19 on banks' efficiency.

Lastly, banks were grouped based on ownership status into 21 domestic and banks 17 foreign ones. The results in Table 8.6 show that domestic banks are found to be more efficient in terms of $\widehat{\widehat{\delta_{\imath,t}}}$ (BCC-BC), with an average of 0.546 compared to 0.526 for the foreign ones over the research period. In contrast, foreign banks recorded a slightly higher efficiency score with an average of 0.450 for the $\widehat{\widehat{\delta_{\imath,t}}}$ (CCR-BC) compared to a value of 0.447 for the domestic ones, which maintained the exact value from 2010 to 2020 and 0.446 in 2021. These results indicate that domestic banks were more efficient regarding variable returns to scale and less efficient for constant returns to scale.

The bank size, ownership structure, and ownership status have been used with other environmental variables in the second data analysis stage to investigate these characteristics' impact on UK commercial bank efficiency. More results discussion on these three variables is presented in the results of the second stage data analysis (regression results) in this chapter. For some reason, the whole sample of this research cannot be divided into sub-samples based on these characteristics for the second analysis stage. First, based on the banks' size (Table 8.4), six large and exceptionally large banks had (total assets of more than £50bn). Second, the same scenario exists regarding ownership structure (Table 8.5), where the publicly quoted banks are nine for the first half of the research period and ten banks for the rest. The results from regression analysis for these two characteristics showed omitted values for most environmental variables, as the number of instruments was higher than the number of cross-sections for all models estimated by GMM models. Roodman (2009) states that there are too many instruments if there are more instruments than cross-sectional units in the panel. For this reason, it is vital to guarantee that the number of instruments is lower than the number of cross-sections for all models estimated by GMM. Third, for ownership status, the results obtained from the DEA efficiency scores (Table 8.6) showed that domestic and foreign banks do not show a significant difference in their efficiency level, indicating the same effect from regression analysis.

Table 8.4: Average scores for the initial technical efficiency ($\widehat{\delta_{\iota,t}}$) and the technical efficiency of the double bootstrap method ($\widehat{\widehat{\delta_{\iota,t}}}$) for the UK commercial banks based on the size from 2010 to 2021.

	Large and exceptionally large banks (Total assets: More than £50bn)					**Small and medium banks (Total assets: Less than £50bn)**				
Year	CCR $\widehat{\delta_{\iota,t}}$	CCR-BC $\widehat{\widehat{\delta_{\iota,t}}}$	BCC $\widehat{\delta_{\iota,t}}$	BCC-BC $\widehat{\widehat{\delta_{\iota,t}}}$	Banks	CCR $\widehat{\delta_{\iota,t}}$	CCR-BC $\widehat{\widehat{\delta_{\iota,t}}}$	BCC $\widehat{\delta_{\iota,t}}$	BCC-BC $\widehat{\widehat{\delta_{\iota,t}}}$	Banks
2010	0.539	0.417	0.911	0.710	6	0.595	0.451	0.632	0.503	21
2011	0.542	0.417	0.910	0.709	6	0.596	0.451	0.633	0.505	22
2012	0.547	0.421	0.910	0.709	6	0.596	0.451	0.633	0.507	23
2013	0.550	0.423	0.910	0.709	6	0.603	0.452	0.640	0.517	27
2014	0.554	0.426	0.910	0.708	6	0.597	0.452	0.635	0.508	29
2015	0.557	0.426	0.911	0.705	6	0.597	0.453	0.637	0.510	32
2016	0.556	0.427	0.911	0.703	6	0.597	0.452	0.636	0.510	32
2017	0.557	0.421	0.911	0.700	6	0.596	0.453	0.636	0.509	32
2018	0.556	0.421	0.908	0.699	6	0.596	0.452	0.634	0.508	32
2019	0.553	0.411	0.908	0.698	6	0.595	0.452	0.633	0.507	32
2020	0.554	0.410	0.908	0.697	6	0.594	0.452	0.632	0.506	32
2021	0.555	0.410	0.908	0.697	6	0.594	0.451	0.631	0.505	32
Mean	0.552	**0.421**	0.910	**0.704**		0.596	**0.452**	0.634	**0.505**	

Note: For the banks' size, banks were divided into two main groups based on total assets. Banks with average total assets of more than (£50bn) over the research period 2010-2021 were considered large and exceptionally large, while banks with average total assets less than (£50bn) were considered small and medium. The six Large and exceptionally large banks in this table are (HSBC Holdings Plc, Barclays Plc, Lloyds Banking Group Plc, NatWest Group Plc, Standard Chartered Plc, and Santander UK Plc). Small and medium banks can be found in Table 8.3, starting from (ID: 7) to the rest of the list. The values of $\widehat{\delta_{\iota,t}}$ (CCR and BCC) and $\widehat{\widehat{\delta_{\iota,t}}}$ (CCR-BC and BCC-BC) are presented in three decimals to show the slight changes in their values during the research period. Sources: Author’s calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

Table 8.5: Average scores for the initial technical efficiency ($\widehat{\delta_{\imath,t}}$) and the technical efficiency of the double bootstrap method ($\widehat{\widehat{\delta_{\imath,t}}}$) for the UK commercial banks based on the ownership structure from 2010 to 2021.

	Publicly quoted banks					**Privately-owned banks**				
Year	CCR $\widehat{\delta_{\imath,t}}$	CCR-BC $\widehat{\widehat{\delta_{\imath,t}}}$	BCC $\widehat{\delta_{\imath,t}}$	BCC-BC $\widehat{\widehat{\delta_{\imath,t}}}$	Banks	CCR $\widehat{\delta_{\imath,t}}$	CCR-BC $\widehat{\widehat{\delta_{\imath,t}}}$	BCC $\widehat{\delta_{\imath,t}}$	BCC-BC $\widehat{\widehat{\delta_{\imath,t}}}$	Banks
2010	0.585	0.439	0.731	0.580	9	0.597	0.451	0.662	0.524	18
2011	0.585	0.440	0.730	0.580	9	0.597	0.449	0.668	0.528	19
2012	0.586	0.440	0.729	0.579	9	0.597	0.449	0.667	0.527	20
2013	0.587	0.441	0.729	0.580	9	0.597	0.449	0.667	0.526	24
2014	0.589	0.442	0.729	0.580	9	0.598	0.450	0.666	0.526	26
2015	0.589	0.443	0.729	0.580	10	0.598	0.450	0.666	0.526	28
2016	0.591	0.444	0.729	0.580	10	0.598	0.450	0.665	0.525	28
2017	0.592	0.445	0.729	0.580	10	0.597	0.450	0.664	0.525	28
2018	0.593	0.446	0.728	0.580	10	0.597	0.450	0.663	0.524	28
2019	0.594	0.447	0.728	0.580	10	0.597	0.449	0.662	0.523	28
2020	0.595	0.448	0.727	0.579	10	0.596	0.449	0.661	0.522	28
2021	0.596	0.449	0.727	0.580	10	0.595	0.449	0.660	0.521	28
Mean	0.590	**0.444**	0.729	**0.580**		0.597	**0.449**	0.664	**0.525**	

Note: The values of $\widehat{\delta_{\imath,t}}$ (CCR and BCC) and $\widehat{\widehat{\delta_{\imath,t}}}$ (CCR-BC and BCC-BC) are presented in three decimals to show the slight changes in their values during the research period. Sources: Author's calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

Table 8.6: Average scores for the initial technical efficiency ($\widehat{\delta_{\imath,t}}$) and the technical efficiency of the double bootstrap method ($\widehat{\widehat{\delta_{\imath,t}}}$) for the UK commercial banks based on the ownership status from 2010 to 2021.

	Domestic banks					Foreign banks				
Year	CCR $\widehat{\delta_{\imath,t}}$	CCR-BC $\widehat{\widehat{\delta_{\imath,t}}}$	BCC $\widehat{\delta_{\imath,t}}$	BCC-BC $\widehat{\widehat{\delta_{\imath,t}}}$	Banks	CCR $\widehat{\delta_{\imath,t}}$	CCR-BC $\widehat{\widehat{\delta_{\imath,t}}}$	BCC $\widehat{\delta_{\imath,t}}$	BCC-BC $\widehat{\widehat{\delta_{\imath,t}}}$	Banks
2010	0.588	0.447	0.692	0.549	13	0.596	0.450	0.662	0.528	13
2011	0.588	0.447	0.691	0.548	15	0.597	0.449	0.669	0.528	13
2012	0.588	0.447	0.691	0.548	15	0.598	0.449	0.669	0.528	14
2013	0.588	0.447	0.690	0.547	17	0.599	0.450	0.669	0.527	16
2014	0.588	0.447	0.690	0.547	18	0.600	0.451	0.669	0.527	17
2015	0.588	0.447	0.689	0.547	21	0.601	0.451	0.669	0.527	17
2016	0.588	0.447	0.688	0.546	21	0.600	0.451	0.668	0.527	17
2017	0.588	0.447	0.688	0.545	21	0.600	0.451	0.667	0.526	17
2018	0.588	0.447	0.687	0.545	21	0.599	0.451	0.666	0.525	17
2019	0.588	0.447	0.685	0.544	21	0.599	0.451	0.665	0.524	17
2020	0.588	0.447	0.684	0.543	21	0.598	0.450	0.664	0.524	17
2021	0.588	0.446	0.683	0.543	21	0.598	0.450	0.663	0.522	17
Mean	0.588	**0.447**	0.688	**0.546**		0.599	**0.450**	0.667	**0.526**	

Note: The values of $\widehat{\delta_{\imath,t}}$ (CCR and BCC) and $\widehat{\widehat{\delta_{\imath,t}}}$ (CCR-BC and BCC-BC) are presented in three decimals to show the slight changes, if any, in their values during the research period. Sources: Author's calculations using annual data from financial statements of 38 UK commercial banks from 2010 to 2021.

8.4 Determinants of bank efficiency (second stage)

This section provides the results of the second data analysis stage, which investigates the factors (bank-specific, industry-specific, and macroeconomic) that affect UK bank efficiency: overall technical efficiency (CCR) and pure technical efficiency (BCC). Following the authors (Stewart, Matousek and Nguyen 2016; Wanke, Barros and Emrouznejad 2016; Du, Worthington and Zelenyuk 2018), this research uses the biased corrected constant return to scale (CCR-BC) and variable return to scale (BCC-BC), which have been generated from first-stage analysis, as the primary measures of bank efficiency.

8.4.1 Descriptive statistics

Table 8.7 presents the summary statistics of the dependent and independent variables used in the empirical models. A wide variety of efficiency measures information is seen. The biased corrected constant return to scale (CCR-BC) and variable return to scale (BCC-BC) values have significant dispersion in the scores, as demonstrated by the minimum, maximum, and standard deviation values. On average, the UK commercial banks show values of 0.45 for CCR-BC and 0.55 for BCC-BC, indicating that UK banks are generally more efficient in terms of variable return to scale (BCC-BC) than constant return to scale (CCR-BC) over the whole period from 2010 to 2021. The mean and standard deviation difference indicates significant differences in the UK commercial banks' efficiency. CCR-BC, with a standard deviation of (0.16), has score values ranging from 0.02 to 0.83, while BCC-BC ranges from 0.02 to 0.88, with a higher standard deviation of (0.20). The wide ranges between these values reflect the fluctuations in banks' efficiency levels during this period and the diversifications of banks used in the research sample.

The independent variables show variations evident by their minimum and maximum values, especially the bank-specific variables (LCR, NSFR, and LOAN) and industry-specific variables (MC). This variation is due to using a sample that includes different banks regarding assets, deposits, capital, and loans. The notable difference among banks in this research sample regards their sizes. Exceptionally large banks, such as HSBC Holding Plc, Barclays Plc, Lloyds Banking Group Plc, and NatWest Group Plc, and other large ones, have the most significant size in total assets, and they use higher capital as they are established for an extended period. In contrast, other banks have small sizes and thus lower deposits, capital, and loans, which downturn their values of the above-mentioned bank-specific ratios. As can be seen from Table 8.7, the most significant values of both mean, and standard deviation among the independent variables are for LCR, NSFR, and LOAN. Their mean values are 234.07%, 186.53%, and 48.69%, while the standard deviation values are 145.03%, 115.91%, and 24.06%, respectively. The other independent (internal) variables of (PVROA, PVNIM, FGR, LOANGR, DEP, DB, and PC) and (external) variables of (INF, GDPG, and COV) have lower values of standard deviation, indicating much more consistency in the data set.

Table 8.7: Summary statistics for all variables employed in the empirical models.

Variables	Obs.	Mean	Std. Dev.	Minimum	Maximum
Dependent variables					
CCR-BC	416	0.45	0.16	0.02	0.83
BCC-BC	416	0.55	0.20	0.02	0.87
Independent variables					
PVROA	416	.72	1.52	-3.42	5.61
PVNIM	416	2.60	2.11	-0.34	9.59
SIZE	416	23.02	2.32	19.18	28.28
FGR	416	-0.06	0.22	-0.72	0.35
LCR	416	234.07	145.03	102	823
NSFR	416	186.53	115.91	81.60	658.40
NPL	416	9.04	28.51	0.01	201.99
LOANGR	416	0.15	0.47	-0.40	2.97
LOAN	416	48.69	24.06	1.60	91.89
DEP	416	0.54	0.24	0.00	0.93
MC	416	48.70	5.98	38.76	57.65
DB	416	0.46	0.49	0	1
PC	416	0.72	0.44	0	1
INF	416	2.92	1.17	0	5.2
GDPGR	416	1.22	3.79	-9.8	6.7
COV	416	0.18	0.38	0	1

Note: CCR-BC; The biased corrected constant return to scale, BCC-BC; The biased corrected variable return to scale, PVROA; Predicted value of the return on assets from previous profitability models, PVNIM; Predicted value of the net interest margin from the previous profitability models, SIZE; Bank size, FGR; Financing gap ratio, NPL; Non-performing loan ratio, LCR; Liquidity coverage ratio, NSFR; Net stable funding ratio, ETR; Effective tax rate, CAR; Capital adequacy ratio, LOANGR; Laon growth ratio, LOAN; Loan specialization ratio, DEP; Deposits ratio, AQ; Asset quality, OE; Operating efficiency, MC; Market concentration, PC; Ownership structure: Dummy variable equals1 for publicly quoted banks, and 0 otherwise, DB; Ownership status: Dummy variable equals1 for domestic banks, and 0 otherwise, INF; Inflation rate, GDPGR; GDP growth rate, COV; Covid-19: Dummy variable equals 1 for the years of (Covid-19) 2020-2021 and 0 otherwise—source of values: Author's calculations.

The MC ratio averages 48.70% and ranges for the sample between 38.76% and 57.65%. The value of this ratio is expected as it is calculated as the sum of the market share of the big four working in the sector, as the concept of "Big Four" exists when referring to the UK banking sector. The maximum value of 57.65 % for MC stands for the year 2021, which indicates that the market is nearly oligopolistic.

8.4.2 Correlation matrix and multicollinearity test for variables

Regression analysis aims to isolate the association between independent and dependent variables. The performance of a regression coefficient is that it describes the mean change in the dependent variable for each 1-unit change in an independent variable when holding all the other independent variables constant.

Multicollinearity appears when independent variables in a regression model are correlated when they are supposed to be independent. If the correlation between variables is high enough, it can cause issues fitting the model and interpreting the results. These problems are that the coefficient estimates can swing wildly based on other independent variables. The coefficients become sensitive to slight changes in the model. Also, multicollinearity lowers the estimated coefficients' precision, weakening the regression model's statistical power. This might lead to unreliable p-values in identifying statistically significant independent variables. Nguyen and Stewart (2020) and Hamid (2017) recommended removing one variable from each pairwise with a correlation coefficient higher than 0.5. This procedure helps to overcome the multicollinearity problems and makes the models for regression analysis more valid and dependable.

Before running the regression analysis, using the GMM, OLS, and EF models, the independence of variables to be secured from multicollinearity problems that may prejudice the results was checked using the correlation matrix. The results show that collinearity problems do not exist between independent variables, as all pairwise independent variables have a correlation coefficient equal to or less than 0.5.

The BCC-BC and CCRBC are correlated with a significant positive value of 0.72. This correlation is expected and not considered a problem as these two dependent variables are measures for efficiency and are run into different models and analysed separately. Table 8.8 presents the correlation coefficient and significance levels between all variables.

Table 8.8: The correlations matrix for the variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1) CCR-BC	1																	
2) BCC-BC	0.72*	1																
3) PVROA	0.08*	0.09	1															
4) PVNIM	0.21	0.07	0.49**	1														
5) SIZE	-0.06	0.43**	-0.03*	-0.29	1													
6) FGR	0.23***	0.29	0.06*	0.10 **	0.14 ***	1												
7) LCR	0.26**	0.06**	0.17**	0.51	-0.36**	0.16**	1											
8) NSFR	0.26**	0.07***	0.17**	0.52*	-0.35***	0.17	0.49**	1										
9) NPL	-0.36	-0.35	-0.00	-0.06	-0.12	-0.37**	-0.03	-0.03	1									
10) LOANG	-0.00**	-0.09	0.04	0.18*	-0.24	-0.05	0.12	0.12	-0.07	1								
11) LOAN	0.48	0.36	0.17**	0.35	-0.05	0.41**	0.21**	0.21*	-0.37*	0.13	1							
12) DEP	0.24	0.09	0.12	0.25	-0.16	-0.50	0.04	0.03	-0.00	0.17	0.56**	1						
13) MC	-0.09	-0.08	-0.04	-0.03***	-0.03	-0.05	-0.09	-0.09	0.08	-0.07	-0.04	-0.00	1					
14) DB	-0.26	-0.38	-0.00	-0.09***	-0.27	0.09	-0.10***	-0.10	0.15	-0.17***	-0.44	-0.54	-0.01**	1				
15) PC	-0.10	-0.43	0.16	0.08	-0.66	-0.11	-0.02	-0.02*	0.11	-0.00	-0.12	-0.03	-0.01	0.44	1			
16) INF	-0.12	-0.06	-0.02	-0.03	0.03	0.04	-0.06	-0.06*	0.02	-0.05*	-0.04	-0.07*	-0.09**	0.01	-0.03	1		
17) GDPGR	-0.05	-0.02**	-0.02	-0.02	-0.01***	-0.01	-0.03	-0.03	0.03	0.04**	-0.01	-0.00	-0.03	0.00	-0.00	0.40	1	
18) COV	0.01**	-0.01	0.07***	0.06	0.04	-0.01	0.04	0.04**	-0.03	0.00	0.01	0.26	-0.00	0.00*	-0.00	-0.04	-0.33	1

Note: The *, **, and *** donate significance at the 10%, 5%, and 1% levels, respectively.

8.4.3 Models and steps used in the regression process

For investigating the determinant of UK commercial banks' efficiency, this research applies the same standard models being used to examine the determinants of bank profitability, namely, the Generalized Method of Moments (GMM), Ordinary Least Squares (OLS), and Fixed Effects (FE) estimators. A detailed explanation of these estimators and their main differences are given in (Chapter 4, Section 4.7, and Chapter 5, Section 5.4). However, this research focuses mainly on the results of the GMM models, as it is the preferred model compared to OLS and EF. A brief reminder of the three standard models is given as follows.

8.4.3.1 Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators

The standard estimators applied to dynamic panel data models, which need to account for cross-sectional fixed effects, indicate the following properties. Firstly, the dynamic models can be consistently estimated when T is large, so dynamic panel bias should not be an issue. Second, the OLS estimator shows dynamic panel bias and is inconsistent when the number of time-series observations (T) is small, even if the number of cross-sectional units (N) is large. Lastly, the coefficient of the lagged dependent variable is upward biased when applying the OLS to a dynamic panel model when T is small. The FE estimator is also biased and inconsistent, as N increases, for small T when using dynamic panel models. The bias and inconsistency of the FE estimator vanish as T increases. Regardless, this estimator can still have a substantial bias (20%) when T = 30 (Roodman 2009).

The coefficient of the lagged dependent variable is downward biased when the FE estimator is used when estimating dynamic panel models with a small T. As these two estimators, OLS and FE, are biased in opposite directions for the coefficient of the lagged dependent variable, both estimators are applied to show a range that the lagged dependent variable's population coefficient is expected to be within. As these two estimators have a sampling distribution that could offset the bias of one or both estimators, the population coefficient may not fall in this range (Roodman 2009).

8.4.3.2 The Generalized Method of Moments (GMM) estimator

The GMM estimators are designed for small T and large N panels. This research applies the difference, and system GMM dynamic panel estimators are consistent as N (though not T) tends to infinity. As the latter is expected to be more suitable for modelling (stationary) near unit root processes than the former (Roodman 2009), considering both supports ensure appropriate modelling of this research's data regardless of the data generation process. For both difference and system GMM methods, the current research applies the one-step estimator (with coefficient standard errors that are robust to autocorrelation and heteroscedasticity) and the two-step estimator (with Windmeijer, 2005, small sample corrected robust coefficient standard errors).

Given that one form of GMM estimator is not unambiguously outstanding from the others, the research considers all four to evaluate their relative performance. While the two-step coefficient estimator is asymptotically efficient and, therefore, superior to the one-step estimator, the two-step coefficient standard errors are biased downwards. However, the Windmeijer (2005) correction dramatically reduces this problem (Roodman 2009).

All regressors except for the lagged dependent variable are assumed to be strictly exogenous because industry-specific or macroeconomic covariates are unlikely to be significantly influenced by individual banks or lagged by one period. All assumed exogenous variables included in a model are used as IV-style instruments. This research appropriately uses the lagged dependent variable as the basis for the GMM-style instruments. As the number of GMM-style instruments equals the number of time-series observations (T), generally, the GMM-style instruments collapsed into one is used to avoid having so many instruments that the instrument equation is overfitted and does not remove the endogeneity of the lagged dependent variable. Roodman (2009) states that using collapsed GMM-style instruments generates a slight loss of estimation efficiency. Regardless, in some instances, the GMM-style instruments will not be collapsed into one to ensure the equations are over-identified.

Hansen's J-statistic assesses instruments' exogeneity, allowing for heteroscedastic and autocorrelated residuals. Regardless, as the number of instruments increases, the test's power falls such that it becomes biased towards accepting the null of exogenous instruments. It is essential to use only a few instruments to avoid overly reducing the power of this test and to ensure the instrumented equation is balanced. Roodman (2009) suggests that there are only so many instruments if there are more instruments than cross-sectional units in the panel. Ensuring that the number of instruments is lower than the number of cross-sections for all models estimated by GMM is vital. Also, for models estimated by GMM to be valid, the following conditions must be met: no second-order autocorrelation and no instrument invalidity.

8.4.3.3 Regression results on environmental variables

In this section, the favoured DEA efficiency scores (as the dependent variable) have been regressed on the environmental variables using the model specified in Equation (7.8), Chapter 7, and the obtained coefficients are shown in n in Table 8.9 and Table 8.10.

Before discussing the analysis results in detail, it is essential to give an overview of the main concepts and abbreviations presented in the mentioned tables. The following section outlines the meanings and values of these concepts and abbreviations.

8.4.3.3.1 An outline of primary results for efficiency models using all estimators

Four versions of the GMM estimator were used, employing the (system) and (difference) estimators with both (one-step) and (two-step) procedures. Due to endogeneity bias (Ullah, Akhtar and Zaefarian, 2018), the results of the analyses indicate significant differences in findings reported under the GMM, OLS, and FE estimators.

In the following tables: Table 8.9 and Table 8.10 for the whole sample data results, Table 8.11 and Table 8.12 for the pre-Brexit sample, and Table 8.13 and Table 8.14 for the post-Brexit sample), 1D and 2D indicate the one and two-step difference estimators and 1S and 2S imply the one and two-step system estimators. Also, the number of observations is noted in the row labelled Obs. The rows labelled (groups) and (instruments) give the number of cross-sectional units and instruments, respectively. For all models estimated by GMM, the number of instruments is below the number of cross-sectional units to avoid the problems associated with using too many instruments. AR (1) and AR (2) present the Arellano and Bond tests for first and second-order autocorrelation, while (Hansen) presents Hansen's test for instrument validity. The null hypothesis of the Hansen test is that the instruments as a group are exogenous. The Arellano and Bond test's null hypothesis is that there is no autocorrelation, and it is applied to the differenced residuals. The AR (2) test in first differences is essential as it detects autocorrelation in levels. A model is considered valid when p-values for all these tests exceed 0.05. As shown in Table 8.9 to Table 8.14, the CCR-BC and BCC-BC models, estimated by the four versions of the GMM estimator (system and difference estimators with both one-step and two-step procedures), exhibit evident second-order autocorrelation or instruments validity as the p-values of AR (2) and (Hansen) exceed 0.05, which indicates that they are valid for inference.

Given the discussion above, estimations in this research are robust and consistent. Also, the insignificant AR (2) tests indicate that error terms do not have second-order autocorrelation. Also, the insignificant Hansen test of over-identifying restrictions (with high p-values) indicates that the models used are accurately specified, assuming there is no evidence of a correlation between instruments and errors.

Tables 8.9 and 8.10 report the efficiency models estimated over the entire sample, including all possible determinants with CCR-BC and BCC-BC as the dependent variables. The lagged dependent variables CCR-BC_{t-1} and BCC-BC_{t-1} are significant at level 0.01 for OLS, FE, and GMM (one and two-step system and one and two-step difference) estimators. These results strongly reinforce the inclusion of these lagged variables in the models and suggest that the OLS and FE estimators will be subject to dynamic panel bias and should not be used for inference. Also, all estimators' coefficients on the lagged dependent variables (CCR-BC_{t-1} and BCC-BC_{t-1}) are between 0 and 1, implying that bank efficiency persists over time. As mentioned earlier, the focus in the discussion of the results is on the GMM estimators' results, and the preference of the appropriate model to be discussed is based on the value of the standard deviation (Std. Err) of the lagged dependent variable. The GMM estimator with the lowest standard error is the preferred one. This method is applied to all GMM estimators for both efficiency measures. Under this method, the GMM estimator (1S), with a standard error (0.135), is preferred for the CCR-BC model, while the (2S) estimator, with a standard error (0.094) is for the BCC-BC model. The following section discusses the results of the efficiency models (CCR-BC and BCC-BC) for the whole sample, estimated by GMM estimators. Results of OLS and FE estimators are also presented in Tables 8.9 and 8.10 for comparison purposes.

Table 8.9: The full sample efficiency model including all variables with CCR-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CCR-BC $_{t-1}$	0.6190*** (13.45)	0.3629*** (5.94)	0.5010*** (3.31) {0.151}	0.6165*** (2.36) {0.260}	0.4853*** (3.57) {0.135}	0.6187*** (2.07) {0.299}
PVROA$_{t-1}$	0.0026 (0.41)	-0.0005 (-0.00)	0.0004 (0.05)	0.0382 (1.25)	0.0039 (0.48)	0.0181 (0.47)
PVNIM $_{t-1}$	-0.0030 (-0.56)	0.0228 (1.24)	-0.0038 (-0.28)	-0.0891 (-1.74)	-0.0029 (-0.39)	-0.0750 (-1.49)
SIZE $_{t-1}$	-0.0017 (-0.34)	0.0308 (2.17)	-0.0052* (-0.52)	-0.0063 (-0.30)	-0.0039* (-0.59)	-0.0002 (-0.01)
FGR $_{t-1}$	0.1278 (0.81)	-0.0451 (-0.11)	0.1377 (0.95)	-0.0343 (-0.18)	0.0973 (0.73)	-0.1537 (-0.43)
LCR $_{t-1}$	-0.0016 (-1.49)	-0.0035 (-1.40)	-0.0023** (-2.16)	-0.0016 (-1.54)	-0.0020*** (-2.57)	-0.0022 (-1.47)
NSFR $_{t-1}$	0.0022 (1.58)	0.0044 (1.37)	0.0031** (2.16)	0.0019 (1.23)	0.0027*** (2.62)	0.0026 (1.27)
NPL $_{t-1}$	-0.0005** (-2.15)	0.0003 (0.83)	-0.0007 (-1.21)	-0.0010 (-1.22)	-0.0007* (-1.90)	-0.0010 (-1.12)
LOANGR $_{t-1}$	0.0165 (1.21)	0.0465*** (2.78)	0.0177 (1.68)	0.0332** (2.49)	0.0116 (0.83)	0.0328* (1.86)
LOAN$_{t-1}$	-0.0005* (-0.36)	0.0001 (0.04)	-0.0007 (-0.57)	-0.0023 (-1.11)	-0.0002 (-0.17)	-0.0004 (-0.13)
DEP $_{t-1}$	0.1282 (0.78)	0.0659 (0.16)	0.1562 (0.89)	0.0375 (0.18)	0.1064 (0.68)	-0.0069 (-0.02)
MC	-0.0006 (-0.56)	-0.0011 (-1.06)	-0.0002* (-0.25)	-0.0014 (-1.59)	-0.0007* (-0.82)	-0.0017 (-1,56)
GDPGR	-0.0004 (-0.22)	0.0000 (0.02)	-0.0005 (-0.27)	0.0019 (0.87)	-0.0003 (-0.11)	0.0001 (0.05)
INF	-0.0099 (-1.63)	-0.0102 (-1.69)	-0.0079 (-1.60)	-0.0135** (-2.14)	-0.0109* (-1.62)	-0.0103 (-1.49)
COV	-0.0254 (-1.59)	-0.0230 (-1.39)	-0.0189 (-0.88)	0.0090 (0.42)	-0.0248 -(0.95)	-0.0035 (0.16)
DB	0.0208 (-1.18)		-0.0196 (-0.76)		-0.0296 (-1.40)	
PC	0.0038 (0.18)		0.0008 (0.02)		-0.0046 (-0.13)	
Constant	0.2338 (1.39)	-0.4282 (-1.22)	0.3427 (1.16)		0.3745 (1.46)	
Obs.	376	376	376	338	376	338
Groups	38	38	38	38	38	38
Instruments			36	24	36	24
AR (1) (p-value)			0.017**	0.043**	0.000***	0.005***
AR (2) (p-value)			0.287	0.336	0.284	0.286
Hansen			0.278	0.615	0.278	0.615

Note: Coefficients and t-statistics (round brackets) are reported. Standard deviations of lagged dependant variables for GMM estimators {curly brackets} are presented. *, ** and *** donate significance at the 10%, 5% and 1% level, respectively. Obs. indicates the total number of observations, while groups represent the number of cross-sectional units. Instruments are the number of instruments. AR (1) and AR (2) denote tests for first and second-order autocorrelation, respectively, while Hansen gives Hansen's J-statistic for instrument validity. OLS denotes the Ordinary Least Square estimator; FE denotes the Fixed Effect estimator; GMM denotes the Generalised Method of Moments estimator; 2S is the two-step system estimator; 2D is the two-step difference estimator; 1S is the one-step system estimator; 1D is the one-step difference estimator. GMM 2D and 1D models use the GMM method without collapsing the GMM-style instruments to ensure the models are over-identified. Sources: Annual financial statements of 38 UK commercial banks from 2010 to 2021.

Table 8.10: The full sample efficiency model including all variables with BCC-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
BCC-BC $_{t-1}$	0.5642 *** (12.24)	0.2403*** (4.10)	0.3611*** (3.72) {0. 094}	0.4324*** (1.87) {0.230}	0.3150*** (3.14) {0.100}	0.3877*** (1.51) {0.256}
PVROA$_{t-1}$	0.0113 (1.48)	-0.0019 (-0.08)	0.0084 (0.72)	0.0326 (0.48)	0.0148 (1.16)	0.0444 (0.85)
PVNIM $_{t-1}$	-0.0036 (-0.56)	0.0723*** (3.24)	-0.001 (-0.12)	-0.0171 (-0.22)	-0.0035 (-0.31)	-0.0001 (-0.00)
SIZE $_{t-1}$	-0.0077 (1.32)	-0.0583*** (3.40)	-0.0161 (1.08)	-0.0111 (0.35)	-0.0129 (1.21)	-0.0058 (0.21)
FGR $_{t-1}$	0.0847 (0.45)	0.0692 (0.15)	0.0592 (0.51)	0.1620 (0.82)	0.1027 (0.75)	0.1120 (0.34)
LCR $_{t-1}$	-0.0019 (-1.44)	-0.0069** (-2.31)	-0.0028*** (-3.31)	-0.0026* (-1.89)	-0.0026*** (-3.21)	-0.0021* (-1.57)
NSFR $_{t-1}$	0.0025 (1.50)	0.0086** (2.29)	0.0036*** (3.35)	0.0032* (1.65)	0.0034*** (3.21)	0.0026* (1.35)
NPL $_{t-1}$	-0.0006** (-2.27)	0.0001 (0.36)	-0.0009 (-1.24)	-0.0006 (-0.73)	-0.0009** (-2.26)	-0.0009 (-1.02)
LOANGR $_{t-1}$	0.0115 (0.72)	0.0473** (2.42)	0.0108 (0.51)	0.0293 (0.85)	0.0029 (0.15)	0.0329 (1.02)
LOAN$_{t-1}$	-0.0002 (-0.16)	-0.0013 (-0.29)	-0.0004 (-0.04)	-0.0022 (-0.89)	-0.0001 (-0.08)	-0.0023 (-0.67)
DEP $_{t-1}$	0.0447 (0.23)	0.0820 (0.17)	0.0283 (0.18)	0.1161 (0.60)	0.0541 (0.36)	0.0594 (0.18)
MC	0.0001 (0.16)	0.0004 0.36)	-0.0010 (-0.93)	-0.0008 (-0.87)	-0.0000 (-0.03)	-0.0005 (-0.50)
GDPGR	-0.0000 (-0.02)	-0.0008 (-0.37)	0.0017 (0.61)	0.0010 (0.53)	-0.0000 (-0.03)	0.0001 (0.06)
INF	-0.003 (-0.50)	-0.0040 (-0.58)	-0.0064 (-0.70)	0.0047 (-0.65)	-0.0068 (-0.86)	-0.0066 (-0.85)
COV	-0.0412** (-2.18)	-0.0577*** (-2.97)	-0.0118 (-0.41)	-0.0353 (-1.17)	-0.0415 (-1.50)	-0.0394 (-1.43)
DB	-.0462** (-2.18)		-0.0706 (-1.52)		-0.0664** (-2.29)	
PC	-0.0157 (-0.61)		0.0026 (0.04)		-0.0359 (-0.70)	
Constant	0.0920 (0.47)	-1.0726** (-2.55)	0.0669 (0.15)		0.1459 (0.47)	
Obs.	376	376	376	338	376	338
Groups	38	38	38	38	38	38
Instruments			36	24	36	24
AR (1) (p-value)			0.004***	0.033**	0.000***	0.004***
AR (2) (p-value)			0.174	0.187	0.165	0.192
Hansen			0.436	0.443	0.436	0.443

Note: See notes to Table 8.7 for variables and Table 8.9 for the other descriptions.

8.4.3.3.2 Results discussion of the whole sample's results

Tables 8.9 and 8.10 present the results of regressions between the independent (environmental) variables and the UK commercial banks' efficiency, measured by CCR-BC and BCC-BC. The results show that, for all GMM estimators, the variables PVROA, PVNIM, FGR, MC, GDPGR, DB, PC, and COV do not appear to be determinants for UK commercial banks' efficiency (CCR-BC and BCC-BC) as the coefficients for all mentioned variables are insignificant. However, this section focuses on the general interpretation of significant essential variables to ease the exposition of the results, mainly the results of the preferred GMM estimators.

In most regression models, it is observed that the lagged dependent variables (CCR-BC_{t-1} and BCC-BC_{t-1}) are positive and significant at the 1% level. As mentioned in the previous section, this strongly supports their inclusion in the models and suggests that the OLS and FE estimators are subjected to dynamic panel bias and should not be the only estimators used for inference. The highly significant coefficient of the lagged dependent variables proves the dynamic character of the model's specification. In the current research, the coefficients of CCR-BC_{t-1} and BCC-BC_{t-1} take values between 0.3150 and 0.6187 for the GMM estimators, which means that efficiency appears to persist to a moderate extent (Dietrich and Wanzenried 2014; Djalilov and Piesse 2016; Le and Ngo, 2020) and indicates that departures from a perfectly competitive market structure in the UK banking sector may not be that large.

Raising total assets seems ineffective for increasing the UK banks' overall technical efficiency (CCR measures) and managerial skills (BCC measures). SIZE, measured as the natural logarithm of a bank's total assets, was found to have negative correlations with efficiency models. It has a significant coefficient in the regression for the CCR-BC efficiency score at 0.10 level; however, it is an insignificant determinant of the BCC-BC efficiency score.

The results are supported by the evidence that the larger the bank is, the harder it will be to manage (Cerasi and Daltung, 2000). Also, larger banks may take more risks due to governments' bailout, commonly called the "too-big-to-fail" policy. The idea behind this is that policymakers will be inclined to bail out institutions considered to be of "systemic" importance, that is, institutions whose potential failure could threaten the stability of the entire financial system (Dávila and Walther 2020). Even after controlling for bank-level characteristics, macroeconomic factors, and the regulatory environment, Sapci and Miles (2019) find that all US banks exhibit rising returns to scale, except the largest (too-big-to-fail). They also analysed the dynamic and bidirectional relationship between bank size and returns to scale. They found that an increase in bank size lowers the chances that a bank can exploit returns to scale.

The regression results of the current research provide additional evidence of the negative link between SIZE and overall technical efficiency. This was also evidenced in the first stage results (Table 8.4), where small and medium UK banks were found to be more efficient regarding the overall technical efficiency (CCR-BC), with an average of 0.452 compared to 0.421 for large and exceptionally large UK banks.

The Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), as Basel III liquidity regulations, have been used in this research to investigate the impact of Basel III on the UK commercial banks' efficiency. Basel III is a set of international banking regulations developed by the Basel Committee on Banking Supervision (BCBS) to strengthen the global banking system and enhance its stability. One of the critical components of Basel III is the introduction of liquidity risk ratios to ensure that banks maintain sufficient liquidity to meet their short-term and long-term obligations, even in times of financial stress.

The LCR, as a tool to ensure that banks can withstand a short-term liquidity crisis, shows an inverse effect on overall and pure technical efficiencies. It has significant negative coefficients for the CCR-BC and BCC-BC efficiency score at 0.01 level. Although the higher the ratio is, the more the bank is seen as being financially stable by investors, the significant adverse impacts of the LCR on the bank's efficiency support the view that UK commercial banks use the LCR at a much higher level than the minimum regulatory requirement. However, high-quality liquid assets represent the most critical component of the LCR, and it is viewed as a measure of liquidity that banks hold; this measure can impact the credit supply. In the context of the UK, Le, Nasir and Huynh (2020) examined the impact of capital requirements under Basel III requirements on bank efficiency of the top five banks (HSBC Holdings, Barclay's Plc, Royal Bank of Scotland Group, Lloyds Banking Group, Standard Chartered Plc). They found a negative relationship between the Basel III ratio and bank efficiency (measured by earnings before interest and tax per total revenues, return on assets, and return on equity).

The current research results provide evidence of the negative relationship between LCR and bank efficiency of the UK commercial banks. Although banks with a high LCR are typically considered safe and likely to meet their short-term financial obligations, a higher level of LCE weakens bank efficiency, both overall technical and pure technical efficiency (RCC-BC and BCC-BC). Regarding the NSFR, the results under the preferred GMM estimator (1S) in Table 8.9 and (2S) in Table 8.10 show highly positive significant associations between NSFR and the CCR-BC and BCC-BC. The coefficients on NSFR are at 0.01 significant level for both efficiency measures. These findings indicate that the higher NSFR favours UK commercial banks' efficiency, as the fund providers prefer banks with satisfactory liquidity. The NSFR has been developed to promote a sustainable and stable structure of assets and liabilities. Based on the positive significant effect of this Basel III ratio, the UK commercial banks comply with the NSFR requirement.

The non-performing loans variable (NPL) is an insignificant determinant of the UK commercial banks' overall technical efficiency CCR-BC). The results align with the expected negative sign as the coefficient on NPL is negative at 0.10 significant level. This result indicates that an increase in NPL negatively affects UK commercial banks’ constant return to scale. The high non-performing loan ratio indicates that a lender is experiencing financial stress and may be unable to meet its obligations to its borrowers. Therefore, lenders must closely monitor this ratio and appropriately address potential issues.

UK commercial banks must limit the acceptable level of NPL ratios, as exceeding these limits might lead to regulatory actions or increased scrutiny. By doing so, the decreasing NPL ratio can be seen as a positive sign and indicates improving loan quality and credit management, which reflect the overall health of the banks’ loan portfolio and their ability to manage credit risk effectively.

The coefficients of the industry-specific variable MC align with the expected sign and show an inverse effect on efficiency measures (CCR-BC and BCC-BC). The MC refers to some businesses and their separate shares of the total production in a market. From a theoretical and practical perspective, market concentration is strongly associated with market competitiveness and is essential to various antitrust agencies when considering offered mergers and other regulatory issues. Various forces, including barriers to entry and existing competition, influence it.

The coefficients on MC indicate the expected sign and show a robust negative with UK commercial bank efficiency. The coefficients are negatively significant in the regression for the overall technical efficiency (CCR-BC) at 0.10. However, it is insignificant for the pure technical efficiency (BCC-BC).

The literature on bank efficiency presents two main hypotheses proposed to define the relationship between market concentration (MC) and bank efficiency. According to Nguyen (2018), the efficient structure hypothesis shows that high market power and more efficient firms represent more concentrated markets. Banks with higher cost efficiency will exceed other banks and ultimately dominate the market. Another hypothesis is the structure conduct-performance hypothesis. It states that more concentrated markets are represented by high-power but less efficient corporations, where banks tend to boost their market power and decrease competition in the market.

Homma, Tsutsui and Uchida (2014) have assessed the efficient structure hypothesis to investigate the efficiency in the banking industry. They find that market concentration reduces banks' efficiency, supporting the so-called quiet-life hypothesis, which writes that companies do not minimise costs in a concentrated market. These findings were supported later by the results of Khan et al. (2017).

The significant negative coefficients in the regression for efficiency measure imply that increasing the concentration in the UK banking sector decreases the overall technical efficiency (CCR-BC). The concentration ratio for the big four UK banks in total assets indicates an oligopoly market structure.

In line with the findings of Semih Yildirim and Philippatos (2007), Homma, Tsutsui, and Uchida (2014) and Khan et al. (2017), this research proves that increasing concentration lowers banks' efficiency, and the leading banks are not necessarily more efficient than other banks. This was also shown in the results of the first stage analysis, where exceptionally large banks were less efficient than small and medium banks. Also, the results of this research align with Sathye (2001), who argues that in highly concentrated markets, risk aversion prevails, making the association between concentration and efficiency negative.

In line with most studies that used inflation as a macroeconomic variable, inflation shows an inverse relationship with the overall technical efficiency (CCR-BC). The coefficients are negatively significant in the regression for the overall technical efficiency (CCR-BC) at 0.10. Regarding the UK economy, the ONS statistics show that the annual inflation rate fluctuated during 2010-2021 (the period of this research) with an average of 3.03%. The rate was 4.6% in 2010 compared to 4.1% in 2021. To maintain the stability of inflation and help businesses and people plan for the future, the UK government set the Bank of England target of inflation of 2%, plus or minus 1% (Bank of England 2022b).

Jiménez-Hernández, Palazzo and Sáez-Fernández (2019) argue that a high inflation rate might generate higher levels of uncertainty regarding economic agents' decisions and lower levels of technical efficiency. The empirical results of the current research indicate that INF affects UK banks' overall technical efficiency (RCC-BC) negatively over the sample period, with a statistically significant coefficient of 0.05. However, an insignificant adverse effect was found with pure technical efficiency (BCC-BC). This result aligns with the argument that an increase in inflation means lowering banks' performance due to higher prices.

8.4.3.3.3 The determinants of UK commercial banks' efficiency before and after Brexit

This research also investigates the impact of Brexit on the UK commercial bank's efficiency. To this end, the whole sample of the research period (2010 -2021) has been divided into two sup-samples: pre-Brexit (2010-2015) and post-Brexit (2016-2021). The efficiency models were analysed using the GMM estimators for consistency with the total sample analysis.

Contrary to the profitability subsamples analysis, the results of GMM estimators for efficiency sub-samples are valid as all lagged dependent variables for both efficiency proxies are found positive and significant. Also, the number of instruments is less than the number of groups in all GMM estimators. The results for the CCR-BC are presented in Table 8.11 and Table 8.12 for the pre-Brexit and post-Brexit samples, respectively. While Table 8.13 and Table 8.14 present the results for pre and post-Brexit samples for the BCC-BC.

Based on the results presented in these four mentioned Tables, the GMM (2S) estimator is the preferred estimator, as it gives the lowest standard error among all GMM estimators for the CCR-BC and BCC-BC, including both subsamples.

Table 8.11: The pre-Brexit sample efficiency model includes all variables with CCR-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CCR-BC $_{t-1}$	0.6994*** (11.22)	0.0986** (1.16)	0.6019*** (4.47) {0.134}	0.3877* (1.58) {0.244}	0.6045*** (4.88) {0.143}	0.3657* (1.52) {0.240}
PVROA$_{t-1}$	0.0100 (0.79)	0.0772** (2.02)	0.0006 (0.05)	-0.0074 (-0.25)	0.0040 (0.25)	-0.0050 (-0.16)
PVNIM $_{t-1}$	-0.0083 (-0.75)	0.0645* (1.82)	-0.0046 (-0.32)	0.0414 (1.16)	-0.0044 (-0.31)	0.0385 (1.09)
SIZE $_{t-1}$	-0.0030 (-0.52)	0.1049*** (5.86)	-0.0045 (-0.35)	0.0759*** (3.42)	-0.0027 (-0.32)	0.0832*** (2.77)
FGR $_{t-1}$	0.1000 (0.52)	0.4642 (0.85)	0.1134 (0.64)	0.4137 (1.12)	0.1334 (0.99)	0.4502 (1.18)
LCR $_{t-1}$	-0.0001 (-0.04)	-0.0005 (-0.03)	0.0001 (0.12)	0.0028 (0.47)	-0.0001 (-0.07)	0.0030 (0.47)
NSFR $_{t-1}$	0.0002 (0.09)	-0.0003 (-0.01)	-0.0001 (-0.06)	-0.0043 (-0.56)	0.0002 (0.14)	-0.0045 (-0.56)
NPL $_{t-1}$	-0.0002 (-1.51)	0.0006* (1.78)	-0.0003** (-2.15)	-0.0001 (-0.34)	-0.0004 (-2.70)	-0.0000 (-0.12)
LOANGR $_{t-1}$	0.0180 (1.35)	-0.0071 (-0.59)	0.0146 (2.75)	0.0125 (1.58)	0.0143 (1.87)	0.0093 (1.02)
LOAN$_{t-1}$	-0.0001 (-0.03)	-0.0039 (-0.73)	-0.0001 (-0.09)	-0.0041 (-1.14)	-0.0002 (-0.27)	-0.0043 (-1.19)
DEP $_{t-1}$	0.0674 (0.33)	0.5108 (0.94)	0.0797 (0.35)	0.3075 (0.77)	0.1033 (0.61)	0.3406 (0.86)
MC	-0.0022(-0.47)	0.0002 (0.04)	-0.0043 (-0.59)	-0.0096 (-1.61)	-0.0037 (-0.75)	-0.0081 (-1.29)
GDPGR	0.0120 (0.54)	0.0195 (0.83)	0.0324 (1.29)	0.0415 (1.76)	0.0217 (0.91)	0.0381 (1.47)
INF	-0.0060 (-0.64)	-0.0032 (-0.35)	0.0014 (0.13)	0.0062 (0.52)	-0.0028 (-0.28)	0.0050 (0.43)
DB			-0.0163 (-0.48)		-0.0230 (-0.88)	
PC			0.0025 (0.04)		0.0131 (0.34)	
Constant	0.2917 (1.10)	-2.0545 (-4.41)	0.4129 (0.96)		0.3679 (1.48)	
Obs.	149	149	149	114	149	114
Groups	35	35	35	33	35	33
Instruments			24	17	24	17
AR (1) (p-value)			0.050**	0.067*	0.044**	0.082
AR (2) (p-value)			0.442	0.155	0.434	0.178
Hansen			0.443	0.880	0.443	0.880

Note: See notes to Table 8.7 for variables and Table 8.9 for the other descriptions.

Table 8.12: The post-Brexit sample efficiency model includes all variables with CCR-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CCR-BC $_{t-1}$	0.4839*** (5.95)	0.0709*** (0.61)	0.2325*** (1.38) {0.168}	0.1109*** (0.55) {0.203}	0.2582***(1.73) {0.207}	0.2875*** (1.31) {0.219}
PVROA$_{t-1}$	0.0001 (0.01)	-0.0177 (-0.32)	-0.0053 (-0.42)	-0.0155 (-0.26)	0.0006 (0.06)	-0.0015 (-0.03)
PVNIM $_{t-1}$	-0.0003 (-0.04)	-0.0290 (-0.55)	0.0077 (0.50)	-0.0387 (-0.42)	0.0007 (0.06)	-0.0864 (-1.22)
SIZE $_{t-1}$	-0.0019 (-0.18)	-0.0918 (-1.51)	-0.0110 (-0.83)	-0.0428 (-0.55)	-0.0057 (-0.44)	-0.0704 (-1.07)
FGR $_{t-1}$	0.1868 (0.55)	0.5353 (0.59)	0.2710** (2.09)	0.1236 (0.39)	0.2516** (2.16)	-0.0635 (-0.19)
LCR $_{t-1}$	-0.0024 (-1.15)	-0.0024 (-0.55)	-0.0038*** (-4.16)	-0.0002 (-0.24)	-0.0032*** (-2.64)	-0.0002 (-0.22)
NSFR $_{t-1}$	0.0031 (1.22)	0.0029 (0.51)	0.0049*** (4.01)	-0.0001 (-0.02)	0.0042*** (2.67)	-0.0000 (-0.02)
NPL $_{t-1}$	-0.0016** (-2.29)	-0.0037** (-2.18)	-0.0021* (-1.85)	-0.0027** (-2.10)	-0.0027*** (-4.00)	-0.0043*** (-3.42)
LOANGR $_{t-1}$	-0.0031 (-0.09)	0.0166 (0.36)	0.0009 (0.03)	0.0659 (1.51)	0.0208 (0.53)	0.0437 (1.05)
LOAN$_{t-1}$	-0.0013 (-0.40)	-0.0067 (-0.77)	-0.0026 0*(-1.83)	-0.0045 (-2.32)	-0.0022* (-1.75)	-0.0035* (-1.71)
DEP $_{t-1}$	0.2354 (0.66)	0.7175 (0.80)	0.4141 (2.09)	0.6075 (1.16)	0.3666 (1.95)	0.4276 (0.90)
MC	-0.0020 (-0.29)	0.0020 (0.29)	-0.0018 (-0.58)	0.0036 (0.60)	0.0017 (0.42)	0.0058 (1.08)
GDPGR	-0.0018 (-0.26)	0.0004 (0.07)	0.0002 (0.08)	-0.0006 (-0.14)	-0.0039 (-0.72)	-0.0039 (-0.84)
INF	0.0009 (0.03)	-0.0252 (-0.77)	-0.0041 (-0.20)	-0.0059 (-0.22)	0.0020 0.08)	-0.0073 (-0.25)
DB	-0.0293 (-0.80)		-0.0338 (-0.89)		-0.0177 (-0.35)	
PC	0.0028 (0.06)		-0.0248 (-0.41)		-0.0228 (-0.43)	
Constant	0.3116 (0.69)	2.7464* (1.47)	0.6269 (1.34)		0.3024 (0.55)	
Obs.	189	189	189	151	189	151
Groups	38	38	38	38	38	38
Instruments			25	18	25	18
AR (1) (p-value)			0.132	0.436	0.000***	0.078*
AR (2) (p-value)			0.351	0.297	0.368	0.367
Hansen			0.181	0.079	0.181	0.079

Note: See notes to Table 8.7 for variables and Table 8.9 for the other descriptions.

Table 8.13: The pre-Brexit sample efficiency model includes all variables with BCC-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
BCC-BC $_{t-1}$	0.5351*** (7.61)	0.0436* (0.57)	0.4714*** (4.38) {0.107}	0.1917* (0.96) {0.199}	0.4005*** (2.82) {0.141}	0.1838* (0.83) {0.222}
PVROA$_{t-1}$	0.0337** (2.03)	0.0263 (0.53)	0.0439 (1.40)	-0.0230 (-0.78)	0.0269 (1.09)	-0.0265 (-0.81)
PVNIM $_{t-1}$	-0.0310** (-2.17)	0.1158 (2.49)	-0.0344 (-1.40)	0.1532** (2.15)	-0.0248 (-1.30)	0.1543 (2.10)
SIZE $_{t-1}$	0.0002 (0.03)	0.1021 (4.13)	-0.0053 (-0.36)	0.0570 (0.92)	0.0060 (0.45)	0.0537 (1.03)
FGR $_{t-1}$	0.1419 (0.56)	0.2522 (0.35)	0.0794 (0.48)	0.2577 (0.60)	0.1272 (0.85)	0.3083 (0.72)
LCR $_{t-1}$	-0.0003 (-0.10)	-0.0279 (-1.20)	0.0010 (0.57)	-0.0243*** (-2.90)	0.0008 (0.37)	-0.0214 (-2.32)
NSFR $_{t-1}$	0.0005 (0.16)	0.0345 (1.19)	-0.0011 (-0.50)	0.0304*** (2.74)	-0.0009 (-0.31)	0.0265 (2.18)
NPL $_{t-1}$	-0.0006** (-2.53)	0.0006 (1.45)	-0.0007*** (-3.31)	0.0000 (0.13)	-0.0006*** (-3.78)	-0.0000 (-0.16)
LOANGR $_{t-1}$	0.0084 (0.48)	0.0105 (0.67)	0.0155 (0.72)	0.0148 (0.55)	0.0123 (0.75)	0.0182 (0.78)
LOAN$_{t-1}$	0.0000 (0.03)	-0.0011 (-0.16)	0.0006 (0.44)	-0.0019 (-0.47)	0.0006 (0.37)	-0.0024 (-0.59)
DEP $_{t-1}$	0.0684 (0.25)	0.1852 (0.26)	-0.0391 (-0.18)	0.1146 (0.24)	0.0200 (0.10)	0.1342 (0.29)
MC	0.0047 (0.74)	0.0076 (0.331)	0.0044 (0.81)	0.0103* (1.69)	0.0033 (0.66)	0.0078 (1.14)
GDPGR	-0.0034 (-0.12)	-0.0197 (-0.65)	0.0081 (0.31)	-0.0206 (-0.78)	0.0031 (0.11)	-0.0116 (-0.39)
INF	-0.0064 (-0.52)	-0.0098 (-0.22)	-0.0036 (-0.28)	-0.0121 (-0.88)	-0.0054 (-0.38)	-0.0099 (-0.39)
DB	-0.0492* (-1.71)		-0.0362 (-0.91)		-0.0566 (-1.56)	
PC	-0.0585 (-1.59)		-0.1190 (-1.89)		-0.0676 (-1.11)	
Constant	0.1106 (0.32)	-2.3415 (-3.75)	0.3240 (0.67)		0.1073 (0.27)	
Obs.	149	149	149	114	149	114
Groups	35	35	35	33	35	33
Instruments			24	17	24	17
AR (1) (p-value)			0.002***	0.038**	0.007***	0.044**
AR (2) (p-value)			0.898	0.837	0.920	0.847
Hansen			0.623	0.809	0.623	0.809

Note: See notes to Table 8.7 for variables and Table 8.9 for the other descriptions.

Table 8.14: The post-Brexit sample efficiency model includes all variables with BCC-BC as the dependent variable using all estimators.

	(OLS)	(FE)	(GMM)			
			2S	2D	1S	1D
Variables	(1)	(2)	(3)	(4)	(5)	(6)
BCC-BC $_{t-1}$	0.4839*** (6.45)	0.1102* (1.07)	0.2711*** (2.66)	0.1822* (1.35)	0.2513** (1.86)	0.2481* (1.49)
			{0.101}	{0.134}	{0. 135}	{0.167}
PVROA$_{t-1}$	0.0070 (0.69)	-0.0318 (-0.56)	0.0105 (0.63)	0.0165 (0.31)	0.0099 (0.70)	0.0221 (0.39)
PVNIM $_{t-1}$	0.0120 (0.15)	0.0525 (0.96)	0.0020 (0.09)	-0.0158 (-0.22)	0.0031 (0.21)	-0.0253 (-0.36)
SIZE $_{t-1}$	0.0120 (1.08)	-0.0996 (-1.61)	0.0076 (0.56)	-0.0191 (-0.26)	0.0156 (1.21)	-0.0545 (-0.79)
FGR $_{t-1}$	0.1434 (0.40)	0.7285 (0.79)	0.3045 (1.55)	0.4818 (1.31)	0.2471 (1.42)	0.3209 (0.95)
LCR $_{t-1}$	-0.0032 (-1.51)	-0.0034 (-0.75)	-0.0044*** (-5.00)	-0.0019 (-1.27)	-0.0045*** (-4.00)	-0.0010 (-0.66)
NSFR $_{t-1}$	0.0042 (1.56)	0.0042 (0.72)	0.0057*** (4.73)	0.0023 (1.07)	0.0057*** (4.02)	0.0009 (0.45)
NPL $_{t-1}$	-0.0009 (-1.25)	-0.0035** (-2.05)	-0.0017** (-2.30)	-0.0023 (-1.58)	-0.0020** (-2.28)	-0.0034** (-2.15)
LOANGR $_{t-1}$	0.0003 (0.01)	0.0025 (0.05)	-0.0010 (-0.03)	-0.0045 (-0.07)	0.0023 (0.06)	0.0004 (0.01)
LOAN$_{t-1}$	-0.0012 (-0.36)	-0.0078 (-0.88)	-0.0037 (-1.89)	-0.0068** (-2.06)	-0.0026 (-1.39)	-0.0063** (-2.06)
DEP $_{t-1}$	0.1645 (0.45)	0.9501 (1.04)	0.4296 (1.68)	1.0307** (1.88)	0.3603 (1.61)	0.8898* (1.87)
MC	0.0020 (0.28)	0.0046 (0.65)	0.0008 (0.23)	0.0035 (0.59)	0.0051 (1.02)	0.0079 (1.39)
GDPGR	-0.0007 (-0.10)	0.0020 (0.29)	0.0006 (0.16)	0.0005 (0.11)	-0.0024 (-0.49)	-0.0037 (-0.76)
INF	-0.0063 (-0.18)	-0.0364 (-1.09)	-0.0075 (-0.38)	-0.0078 (-0.29)	-0.0080 (-0.29)	-0.0057 (-0.18)
DB	-0.0365 (-0.95)		-0.0392 (-0.68)		-0.0337 (-0.67)	
PC	0.0017 (0.04)		-0.0273 (-0.42)		-0.0248 (-0.40)	
Constant	-0.0686 (-0.15)	2.7058* (1.81)	0.2238 (0.50)		-0.1536 (-0.32)	
Obs.	189	189	189	151	189	151
Groups	38	38	38	38	38	38
Instruments			25	18	25	18
AR (1) (p-value)			0.017**	0.123	0.021**	0.040**
AR (2) (p-value)			0.540	0.400	0.483	0.472
Hansen			0.478	0.236	0.478	0.236

Note: See notes to Table 8.7 for variables and Table 8.9 for the other descriptions.

The results for pre-Brexit, as presented in Table 8.11 and Table 8.13, show that NPL is the only variable that has a significant association with both efficiency measures CCR-BC and BCC-BC. The coefficients are negative at 0.05 significant level for CCR-BC, while at 0.01 for BCC-BC. These results indicate that the NPL is affecting the UK commercial banks' pure technical efficiency at a higher level than its effect on the overall technical efficiency. However, the results for the post-Brexit analysis show that the level of negative significant effect of NPL is less for both efficiency measures, being at 0.10 for CCR-BC and at 0.05 for BCC-BC.

The LCR and NSFR are significant determinants of the UK commercial banks' efficiency measures CCR-BC and BCC-BC for the post-Brexit data analysis. The results align with the results of the whole sample regarding the effect sign and the significant level.

The results presented under the preferred GMM estimators (S2) in Table 8.12 show that the LOAN ratio (measured as the bank's outstanding loans as a percentage of its total assets) is negatively associated with efficiency measure (CCR-BC) for the post-Brexit data analysis. Although a higher loan ratio means a better credit performance level because loans are a significant part of the assets' total structure, it could negatively affect liquidity since a higher ratio value means existing funds are widely used for credit funding and less for short-term liabilities. The higher the loan-to-asset ratio, the riskier a bank may be to have higher defaults. Since loans supply the highest return on banks' assets, loans are expected to positively influence performance if banks do not take on an unacceptable risk level, reflecting a bank's efficiency level. According to Olson and Zoubi (2011), the loan ratio is sometimes used to measure liquidity risk or asset utilization ratios. The earlier investigations, such as Jiménez-Hernández, Palazzo and Sáez-Fernández (2019), find that the loans-to-assets ratio is negatively associated with cost efficiency but positively associated with revenue efficiency. The results of this research reflect UK banks' management skills in managing their outstanding loans, indicating that increasing the loan ratio should be at most an optimal level; otherwise, the bank becomes loaned up and subjected to risk default as its liquidity decreases.

8.5 Summary

This chapter presented the results of investigating the efficiency of the UK commercial banks. For the first part of data analysis, within this research method, a set of relevant environment-independent inputs and outputs were specified for the DEA analysis (first stage). These inputs and outputs were first performed to compute the relevant efficiency scores for the analysis considering the overall technical efficiency (CCR) and pure technical efficiency (BCC) by solving the proper DEA models. In the second stage, Simar and Wilson's (2007) procedure has been applied to bootstrap the DEA scores with bootstrapped regression. In this stage, the bias-corrected (Algorithm 2) is used as it is preferred and used for inference (Simar and Wilson, 2007). The estimated efficiency scores from this stage have been used as dependent variables for the second part of the data analysis, where twelve econometric models (one model of OLS and FE and four GMM models for each proxy of efficiency) were used to examine the relationship between the UK banks' efficiency (overall technical efficiency and pure technical efficiency as proxied by RCC-BC and BCC-BC) and the presumed environmental explanatory variables.

To understand the UK commercial banks' overall technical efficiency, banks for the first part of the analysis in this research were classified into three groups based on their characteristics (size, ownership structure, and ownership status). For comparison purposes between UK commercial banks, Table 8.4, Table 8.5, and Table 8.6 were created based on the bootstrapped estimated efficiency scores presenting the average scores for the initial technical efficiency and the technical efficiency as the double bootstrap method for the UK commercial banks based on bank size, ownership structure and ownership status, respectively.

The results obtained from the first part of the data analysis show that small and medium banks were more efficient than large and exceptionally large banks regarding the constant returns to scale, as they have a larger average value of CCR-BC of 0.452 compared to a value of 0.421 for large and large banks. In contrast, large and exceptionally large banks have a more significant value of 0.704 for pure technical efficiency than 0.505 for small and medium banks. The results also show that publicly quoted banks maintain a (BCC-BC) of 0.580 for 2010-2021, showing more efficiency over the privately-owned banks with 0.525 on average for the same period. Also, domestic banks were more efficient regarding BCC-BC, with an average of 0.546 compared to 0.526 for the foreign ones over the research period. In contrast, foreign banks recorded a slightly higher efficiency score with an average of 0.450 for the CCR-BC compared to a value of 0.447 for the domestic ones, which supported the exact value from 2010-2021. These results show domestic banks were more efficient with variable returns to scale and less efficient with constant returns.

The regression analysis results of the whole, pre and post-Brexit samples show that the lagged dependent variable CCR-BC_{t-1} and BCC-BC_{t-1} positive and significant for OLS, FE, and GMM (one and two-step system and one and two-step difference) estimators. Also, all estimators' coefficients on the lagged dependent variables (CCR-BC_{t-1} and BCC-BC_{t-1}) were between 0 and 1, implying that bank efficiency persists over time. These results strongly reinforce the inclusion of these lagged variables in the models and suggest that the OLS and FE estimators will be subject to dynamic panel bias and should not be used for inference.

For the whole sample data analysis, results under the preferred GMM estimators (1S) in Table 8.9 indicate that SIZE, LCR, NSFR, NPL, MC, and INF are significant determinants of the UK commercial banks' overall technical efficiency (CCR-BC). Also, the results under the preferred GMM estimator (2S), in Table 8.10, show that LCR and NFSR are significant determinants for the UK commercial banks' pure technical efficiency (BCC-BC).

The results of GMM estimators for efficiency sub-samples are valid as all lagged dependent variables for both efficiency proxies are found positive and significant. The results for the CCR-BC were presented in Table 8.11 and Table 8.12 for the pre-Brexit and post-Brexit samples, respectively. While Table 8.13 and Table 8.14 presented the results for pre and post-Brexit samples for the BCC-BC.

Based on the results presented in these four mentioned Tables, the GMM (2S) estimator is the preferred estimator, as it gives the lowest standard error among all GMM estimators for the CCR-BC and BCC-BC, including both subsamples. The results for pre-Brexit, as presented in Table 8.11 and Table 8.13, show that NPL is the only variable that has a significant association with both efficiency measures CCR-BC and BCC-BC. The LCR and NSFR are significant determinants of the UK commercial banks' efficiency measures CCR-BC and BCC-BC for the post-Brexit data analysis. Based on the present research findings, the following chapter (Chapter 9) gives implications and recommendations to UK commercial banks, investors, lenders, and policymakers.

Chapter 9: Concluding Remarks

9.1 Introduction

The primary purpose of this research was to empirically investigate the UK commercial banks' financial performance in terms of profitability and efficiency during unstable market conditions. The research applied the Generalised Method of Moments GMM (system and difference) estimator for both performance measures (profitability and efficiency) using a unique dataset of 38 UK commercial banks from 2010 to 2021. The research aims addressed are set as follows. Firstly, the research assessed the bank-specific, industry-specific, and macroeconomic determinants of UK commercial banks' profitability for the whole sample. Second, it investigated the determinants of UK commercial banks' profitability before and after Brexit by dividing the research period into before and after 2016. Third, it measured the overall efficiency level of UK commercial banks by using a set of inputs and outputs to generate the efficiency scores. Fourth, it provided a comprehensive discussion of the UK commercial banks' characteristics and how they affect their efficiency by classifying banks into three groups based on their characteristics (size, ownership structure, and ownership status). Lastly, it investigated the determinants of the UK commercial banks' efficiency for the whole, pre and post-Brexit samples using the bank-specific, industry-specific, and macroeconomic variables used in the profitability analysis. The results of applying the Ordinary Least Squares OLS and Fixed Effects FE estimators have been presented for comparison purposes.

The sample in this research included publicly quoted, privately owned, domestic, foreign, large, exceptionally large, and small and medium commercial banks working in the UK banking sector. Due to entry and exit within the UK Banking sector, the year of incorporation of the banks in this research sample in the UK banking sector and the availability of their annual financial data led to unbalanced panel data with 416 observations for the whole sample. The current research is the first to specify a precedent in determining, at the same time, the key drivers of both profitability and efficiency of the UK commercial banks. Concerning earlier studies discussed in chapters of literature focused on the banks' performance drivers, the contribution of the current research provides the literature to understand the profitability and efficiency of UK commercial banks during a specific period of the economic cycle and, more significantly, during a period of financial instability, including events such as the period following the global financial crisis, Basel III, Brexit, and Covid-19. Also, it provides a baseline for UK commercial banks to appropriately manage fiscal crisis periods by dedicating their financial resources to the areas that positively impact their profitability and efficiency.

9.2 Summary of thesis chapters

Chapter 1 presented the introduction of the whole thesis. The chapter provided a background on the most critical financial and economic events the UK economy and financial sector have experienced from 2010-2021. Then, it addressed the motivations and contributions of conducting this research. The chapter also presented the research objectives of examining the UK banking sector's performance (profitability and efficiency). Lastly, it gave the reader guidance on the structure of the thesis by summarising the essential information presented in each chapter of this thesis.

Chapter 2 presented a background of the UK banking sector. The chapter started with a brief description of the UK financial system, then moved to introduce the UK banking sector. Moreover, the chapter provided an overview of the monetary financial institutions, including the central bank (BoE), UK banks, and UK building societies. The chapter also presented the UK Financial Regulators, covering the Bank of England (BoE), the Financial Policy Committee (FPC), the Financial Conduct Authority (FCA), the Prudential Regulation Authority (PRA) and Her Majesty's Treasury (HM Treasury). Lastly, the chapter has shed light on recent financial and economic events, such as the Global Financial Crisis and the UK responses to its effects, Basel III, Brexit, and the Covid-19 pandemic.

Chapter 3 reviewed the recent studies on bank profitability and its determinants. The chapter started with introducing the concept of profitability to give the reader a better understanding of the concept before moving to the rest of the chapter. Then, the chapter comprehensively explained profitability from a firm's perspective and how it is considered a financial performance indicator. Furthermore, the section on profitability measurement explained how profitability is measured by presenting the most used financial ratios by giving brief information about each ratio and how it is calculated. Lastly, the chapter discussed the literature on bank profitability by addressing the studies on this topic. It detailed the regions, data samples, variables, and the results of these studies.

Chapter 4 explained the methodology for investigating UK commercial banks' profitability determinants. The chapter was organised into sections presenting the research questions and the research hypothesis. Then, it presented the research philosophy, approach, data type, and collection method. Furthermore, it presented the research period, sample, and data. It also provided a detailed explanation of the determinants of bank profitability and variable selection. This section has two subsections for the profitability measures (dependent variables) and the determinants of banks' profitability (independent variables). The determinants of banks' profitability were classified into bank-specific, industry-specific, and macroeconomic factors. The Ordinary Least Squares (OLS) and Fixed Effects (FE) have been presented in the section on standard estimators. The chapter also presented the econometric specification of the dynamic panel system GMM model used for analysing the data. Lastly, it presented the data analysis method. The chapter included two comprehensive tables. The sample of the UK commercial banks used in the research, including their total assets, market shares compared to the whole UK banking sector and their specialisations, and the number of observations for each bank, was presented in Table 4.1. A summary of the dependent and independent variables, their descriptions, and their expected effect on banks' profitability is presented in Table 4.2.

Chapter 5 focused on the empirical data analysis of commercial bank profitability. Thirty econometric models (one model of OLS, FE, and GMM models for each proxy of profitability) were used to investigate the association between the UK banks' profitability (Return on assets, return on average assets, return on equity, return on average equity, and net interest margin as proxied by ROA, ROAA, ROE, ROAE, and NIM, respectively) and the presumed internal and external explanatory variables. The chapter illustrated the econometric results of the regression analysis using the OLS, FE, and GMM models for the whole sample and the OLS estimator for the pre and post-Brexit samples due to the invalidity of the GMM results. It presented the descriptive statistics for the variables used in the regression analysis, then the correlation matrix and the test for multicollinearity. Moreover, it presented the models and steps used in the estimation process. Lastly, the chapter comprehensively discussed the regression analysis results for all samples.

Chapter 6 reviewed the existing literature on bank efficiency and its determinants. The chapter introduced the concept of efficiency and its drivers to give the reader a better understanding before moving to the rest of the chapter. It explained the efficiency types, including scale efficiency, X-efficiency, technical efficiency, pure technical efficiency, allocative efficiency, and other types, such as cost efficiency and scope efficiency. The chapter comprehensively explained the measures of banking efficiency. The structural and non-structural measures were explained in the first part of that section. The non-structural approach compares performance among banks using different financial ratios. The second part of the section presented the Traditional, Parametric, and Non-Parametric Measures. The traditional method of measuring efficiency uses ratio analysis from several financial institutions. The parametric method, known as "parametric programming", is concerned with the production or expense function base. It is used to estimate the characteristics of the function and measure economies of scale with the assumption that all decision-making units (DMUs) operate efficiently. It can be classified into three distinct categories: The Stochastic Frontier Approach (SFA), The Thick Frontier Approach (TFA), and The Distribution-Free Approach (DFA). The non-parametric method is also known as the "non-parametric programming approach". The Data Envelopment Approach (DEA) is the most common non-parametric efficiency measure. Lastly, the chapter discussed the existing literature on bank efficiency by addressing the studies conducted on this topic. It showed the regions, data samples, models for analysis, input and output variables, and the results of these studies in detail. Also, a summary of some recent studies on bank efficiency is presented in Table 6.1.

Chapter 7 presented and explained the methodology and method of investigating the overall efficiency and its determinants in UK commercial banks. The chapter was organised into sections presenting the research questions. Also, it presented the research philosophy and approach, the data type, and the collection method. Moreover, it presented the research methodology through subsections where the CCR and BCC models, the bootstrap two-stage procedure, the first-stage DEA efficiency estimate, and the second-stage regression were discussed in detail. The chapter also provided an explanation of the specification of the inputs and outputs and the specification of the dependent and independent variables that were used for the data analysis. The chapter included three primary tables presenting valuable information. Table 7.1 presents the CCR and BCC models. Table 7.2 provides definitions and descriptions of the selected input and output variables used for the first part of the analysis to generate the efficiency scores. Lastly, Table 7.3 presents the descriptions and the expected effect of the variables employed in the second part of the analysis. These variables were classified into bank-specific, industry-specific, and macroeconomic factors.

Chapter 8 discussed the results of investigating the efficiency of the UK commercial banks. For the first stage analysis, relevant environment-independent inputs and outputs were specified for the DEA analysis within this research method. These inputs and outputs were first performed to compute the relevant efficiency scores for the analysis considering the overall technical efficiency (CCR) and pure technical efficiency (BCC) by solving the proper DEA models. The estimated efficiency scores from this stage have been used as dependent variables for the second data analysis stage. For the second stage, twelve econometric models (one model of OLS and FE and four GMM models for each proxy of efficiency) were used to examine the relationship between the UK banks' efficiency (overall technical efficiency and pure technical efficiency as proxied by RCC-BC and BCC-BC) and the presumed environmental explanatory variables.

9.3 Summary of findings for profitability and efficiency results

To the best of the author's knowledge, this is the first comprehensive research directed at investigating the performance of UK commercial banks by examining the determinants of their profitability and efficiency using the GMM (employing the (system) and (difference) with both (one-step) and (two-step) procedures, OLS, and FE estimators. The general significance of the lagged dependent variables in the results of regressions for profitability and efficiency suggests the need to account for dynamic effects and justifies using such estimators. This research also extends the previous literature by considering additional factors, namely, Basel III liquidity ratios, Brexit, and Covid-19, not employed in previous studies of UK commercial banks’ profitability and efficiency. The current results use a larger sample in terms of the number of banks and periods compared to any previous analysis of the UK banking system (Data for 38 UK commercial banks, consisting of 416 observations for 2010-2021). The empirical results of this research indicate that the GMM estimator is more efficient than the OLS and FE estimators.

9.3.1 Results of profitability analysis

The main findings of this research are presented in Table 5.3, Table 5.4, Table 5.5, Table 5.6, and Table 5.7 for the entire sample and in Table 5.8 and 5.9 for the pre and post-Brexit samples, respectively. Based on the preferred GMM estimator for each profitability model mentioned in Section 5.5.1 of Chapter 5, the results show that bank-specific variables, SIZE, NPL, LOANGR, OE, and COV, are significant determinants of UK commercial banks' profitability.

For SIZE, these results are in line with previous studies that applied the GMM models, such as Kosmidou, Tanna and Pasiouras (2008), Dietrich and Wanzenried (2011) and Le, Nasir and Huynh (2020), who found a negative association between bank size and the stated profitability measures. The results are supported by the evidence that the larger the bank is, the harder it will be to manage (Cerasi and Daltung 2000). Also, larger banks may take more risks due to governments' bailouts. The idea behind this is that policymakers will be inclined to bail out institutions considered to be of "systemic" importance, that is, institutions whose potential failure could threaten the stability of the entire financial system (Dávila and Walther, 2020). In the context of the UK, the results of the current research are consistent with the findings of Kosmidou et al. (2006), who compare the performance of UK banks over the period 1998- 2002, and Kosmidou, Tanna and Pasiouras (2008), who investigate the impact of bank-specific characteristics, macroeconomic conditions and financial market structure on the UK owned commercial banks' profits, during the period 1995-2002. Their findings were that smaller banks are more profitable and perform better than larger banks. Grose et al. (2021) analysed bank profitability in a sample of UK commercial banks from 2007–2018. They found that bank size has a negative role in profitability due to the existence of economies of scale for the smaller banks and diseconomies for the larger ones.

In line with previous findings of Ciukaj and Kil (2020) and Ozili (2019), the results shown under the 2D estimator for ROA and ROAA and 2S for NIM exhibit that NPL is negatively associated with bank profitability. The NPL ratio threatens commercial banks' financial stability and the national monetary security system. Commercial banks will lose much capital when bad debts exceed the permitted limit. This affects cash flows, and banks will become illiquid, leading to possible bankruptcy and risk to banks' sustainable development and profitability.

Bad debt reduces profits due to risks that lead to many financial losses. Credit is the fundamental activity of the bank, bringing in the primary revenue source. However, the revenue from credit activities entailed credit risks. The unrecovered debt causes commercial banks' capital to diminish, leading to difficulty in making a profit. Studies from Andries (2011), Banker, Chang and Lee (2010), Athanasoglou et al. (2008) and Demirgüç-Kunt and Huizinga (1999) conclude that when the NPL ratio increases, the bank's profitability will be decreased. The current research results recommend that instead of focusing on lending, UK commercial banks should focus more on screening and monitoring the loan default risk to maximise their profit-making ability.

LOANGR has a significant positive statistical effect on UK commercial banks' NIM. The result is in line with Le (2020), Dang (2019), and Al-Khouri and Arouri (2016), indicating that profitable banks are more likely to raise credit since they can attract more funds. Also, the bank's lending expansion generally causes better profitability. The current research recommends that UK commercial banks keep the growth rate in loans at the optimal level, as excessive loan growth may lead to more significant risks through increasing the NPL, which could be translated to a decrease in bank profitability.

Regarding OE, the cost-to-income ratio, the variable's coefficients negatively impact UK commercial banks' profitability: ROA, ROAA, ROE, and ROAE. The coefficients on OE are highly statistically significant at a 0.01 level for all mentioned profitability measures. A high cost-to-income ratio may indicate that a bank is not efficiently managed or that a high competition level exists in the banking industry. As the calculations of this ratio depend on cost and income figures, banks could lower the ratio's value by either increasing their operating revenues or decreasing their operating expenses. The significant negative results align with the results of (Athanasoglou, Brissimis and Delis 2008; Dietrich and Wanzenried 2011).

DEP positively affects profitability, with significant coefficients for ROA and NIM models. The positive results found in this research meet the expected positive sign and confirm the findings of Saeed (2014) and Lee and Hsieh (2013), indicating that increasing customer deposits leads to a growth in the funds available for different profitable opportunities such as lending and investments; consequently, increasing banks' profitability. However, if banks cannot release money through loans, their profitability level decreases due to paying interest to depositors on their fixed, time, or term deposits. It could be recommended that UK commercial banks hold optimal deposits, which can be transferred into high-quality loans, hence gaining profits.

The macroeconomic variable COV is found to impact NIM significantly. The impact of COV on NIM for the UK commercial banks is small, at the 10% significance level. This weak negative correlation indicates the ability of the UK government and the Bank of England to provide a plan that could weaken the significant impact of the pandemic on the UK economy in general. The response of the Bank of England to the pandemic was clear and compelling. The BoE was performed to save jobs and support the UK economy through measures and determinations. According to the Bank of England (2020a), in March 2020, the BoE cut its interest rate (Bank Rate). The cut in the Bank Rate offered the UK banks and building societies long-term funding at interest rates of 0.1%. This results in cheaper loans for businesses and households. That reduced the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households.

For all profitability models, ROA, ROAA, ROE, ROAE and NIM, with all GMM estimators, the bank-specific variables LCR, NSFR, ETR, LOAN and the industry-specific and macroeconomics variables MC, PC, INF, GDPGR (except for ROA and ROAA), COV (except for NIM) do not appear to be determinants for UK banks profitability as the coefficients for all mentioned variables are insignificant.

9.3.2 Results of efficiency analysis

To stand on the UK banks' overall technical efficiency, banks for the first part of data analysis in this research were classified into three groups based on their characteristics (size, ownership structure, and ownership status). For comparison purposes between UK commercial banks, Table 8.4, Table 8.5, and Table 8.6 were created based on the bootstrapped estimated efficiency scores presenting the average scores for the initial technical efficiency and the technical efficiency as the double bootstrap method for the UK commercial banks based on bank size, ownership structure, and ownership status, respectively. The results obtained from the first stage analysis show that small and medium banks were more efficient than large and exceptionally large banks regarding the constant returns to scale, as they have a larger average value of CCR-BC being 0.452 compared to a value of 0.421 for large and large banks. In contrast, large and exceptionally large banks have a more significant value of 0.704 for pure technical efficiency than 0.507 for small and medium banks. The results also show that publicly quoted banks maintain a (BCC-BC) of 0.580 for 2010-2021, showing more efficiency over the privately-owned banks with 0.525 on average for the same period.

Domestic banks were more efficient regarding BCC-BC, with an average of 0.546 compared to 0.526 for the foreign ones over the research period. In contrast, foreign banks recorded a slightly higher efficiency score with an average of 0.450 for the CCR-BC compared to a value of 0.447 for the domestic ones, which supported the exact value from 2010-2021. These results show domestic banks were more efficient with variable returns to scale and less efficient with constant returns. The second stage (regression analysis) results show that the lagged dependent variable CCR-BC_{t-1} and BCC-BC_{t-1} were significant at level 0.01 for OLS, FE and GMM (one and two-step system and one and two-step difference) estimators. Also, all estimators' coefficients on the lagged dependent variables (CCR-BC_{t-1} and BCC-BC_{t-1}) were between 0 and 1, implying that bank efficiency persists over time. These results strongly reinforce the inclusion of these lagged variables in the models and suggest that the OLS and FE estimators will be subject to dynamic panel bias and should not be used for inference. For the whole sample data analysis, results under the preferred GMM estimators (1S) in Table 8.9 indicate that SIZE, LCR, NSFR, NPL, MC, and INF are significant determinants of the UK commercial banks’ overall technical efficiency (CCR-BC). Also, the results, under the preferred GMM estimator (2S) in Table 8.10, show that LCR and NFSR are significant determinants for the UK commercial banks’ pure technical efficiency (BCC-BC). The results for pre-Brexit, as presented in Table 8.11 and Table 8.13, show that NPL is the only variable that has a significant association with both efficiency measures CCR-BC and BCC-BC. The LCR and NSFR are significant determinants of the UK commercial banks' efficiency measures CCR-BC and BCC-BC for the post-Brexit data analysis; see Table 8.12 and Table 8.14.

9.4 Policy implications

Investigating the profitability and efficiency of UK commercial banks can be helpful for policymakers, bank managers, and market analysts. Regarding customers, bank investors prefer dealing with profitable and efficient banks that can provide better services and interest rates than other banks. Consequently, UK banks are recommended to better upper their management strategies to raise the possibility of performing better profitability and efficiency. This action requires UK banks to hire professionals and proficient managers to take banks onward with efficient and profitable decisions. Also, to have the capability to deal with unexpected, challenging events.

Regarding the determinants of profitability and efficiency, the positive or negative effect of internal (bank-specific) variables allows banking regulators to put strategies to raise profitability and efficiency. At the same time, the impact of external (industry-specific and macroeconomic) variables makes banks able to invest more by establishing more or fewer branches within the country. The allocation of resources can be used to build the banking sector to prosper and aid economic development within the UK. This research demonstrates the critical variables required to be in place to present UK banks with the opportunity to optimise performance (profitability and efficiency).

The current research's findings aid UK policymakers' understanding of what determines the profitability and efficiency of the banking sector, as a leading sector in the financial system that contributes to the overall economy. Policymakers may develop relevant and fair regulations to guarantee monetary stability and facilitate the banking sector to optimise profitability and efficiency. The expanded capital requirement regulations from the Bank of International Settlements (Basel III) negatively affected the UK banks' profitability and efficiency. The capital-required regulations directly impact the banking sector by restricting banks from taking excessive risks. This decreases the ability of banks to reach their full potential.

The negative impact of inflation requires UK policymakers to put extra effort into reducing its impact. Although the UK government sets the Bank of England inflation at a target of 2%, plus or minus 1% (Bank of England 2022b), the actual rate is still higher than the target, increasing yearly—this increase in inflation results in lowering banks' performance due to higher prices. It is recommended that enhancing and continuing the liquidity support and aid programs contribute to moderating the negative impact of the crisis and help UK banks maintain their efficiency; however, this should be at most at a level where it will not negatively impact the ability to control inflation. This has been confirmed by the results of this research, where it was found that the clear and convincing response of the Bank of England to the pandemic was achieved by saving jobs and supporting the UK economy through measures and determinations. In response to the pandemic's start, the BoE, in March 2020, cut its interest rate (Bank Rate) and offered the UK banks and building societies long-term funding at interest rates of 0.1% (Bank of England 2020a). This resulted in cheaper loans for businesses and households, which decreased the costs faced by businesses and households in the UK during the pandemic. Also, the BoE helped the UK banks to expand their lending power by reducing the weight of financial resources (capital) that banks and building societies needed to set against their lending to UK businesses and households. Another policy implication is that, in the event of a future financial system crisis, central banks might be best served by boosting their open market operations and raising liquidity facilities to financial institutions within the financial system rather than increasing their lender-of-last-resort activity.

9.5 Limitations and other challenges

The studies performed within this thesis present some limitations and challenges throughout the empirical chapters. The research's overall picture has only covered the commercial banks' performance within the UK. It has yet to concentrate on other financial institutional performances, such as UK building societies, as the latter's data was unavailable for some years within the research period. This made it difficult to have a sample that included building societies. Most essential internal independent variables for profitability and efficiency investigations have been calculated using various financial ratios requiring many annual figures. Also, some banks' annual financial reports were not published on the Orbis Bank Focus database, and some data were missing for other banks. This led to searching for the original documents and going through them to find the data needed. Some of the annual reports were in picture format instead of PDF, which was another challenge in searching for the required data. Also, some foreign banks in the UK banking sector published annual reports on their home currency, so the exchange rates for each year (2010-2021) against the Sterling Pound were needed to get the financial numbers and values in (£) before calculating variables.

Furthermore, to get more valid results that reflect the impact of Covid-19 and Brexit on the banking sector, it was required to wait until the research sample's annual reports were published or were available on the banks' websites so that the data for the year 2021 could be collected. Another limitation is that this research only focuses on bank profitability ratios to measure UK commercial banks' performance. The UK commercial banks' market performance (measured by Tobin's Q) could not be investigated as it is calculated by dividing a bank's market value by its assets' replacement cost. This ratio is eliminated from this research due to the unavailability of market value data for most private UK commercial banks included in this research, so it was impossible to use this ratio to measure UK commercial banks' market performance. However, this thesis produced the best results that could be generated for profitability and efficiency with the available resources for UK commercial banks included in this research from 2010 to 2021.

9.6 Directions for future research

The issues covered in this thesis across the UK commercial banks are only the beginning of the literature regarding such a topic in a current context. An additional investigation could approve or reject the results and policy implications of completing this thesis. First, investigating financial performance (profitability and efficiency) can be enhanced from the academic world by adding more banks and other private financial institutions, such as building societies within the data sample, which may deliver further transparency and add other dimensions to the field of financial performance. This is an ideal possibility for enriching the existing literature on the topic and contributing to knowledge. With a greater comprehension of the determinants of banks' financial performance (profitability and efficiency), the implemented policies can be adapted, creating more stability in the sector and maximising the banks' financial performance.

Furthermore, examining commercial banks' financial performance can be applied to other economies as a possibility for further research and comparative research. Second, the research can be furthered by undertaking the same or different methodologies by adding more environmental factors to what has been applied within this research. This could create different outcomes and cause a debate in the literature on financial performance (profitability and efficiency). Expanding the research period in future works could give more counted results regarding the impact of Covid-19 on commercial banks' profitability and efficiency. As the financial sector could take longer to reflect the effect of the pandemic as a microeconomic event, using data for a more extended period covering 2020 to 2025 could give more evident results on the impact of Covid-19. Third, with the improvement of Internet technology, e-banking and mobile banking have been growing as it is more convenient and cost-effective. Considering technology variables, future research could be undertaken on UK commercial banks' profitability and efficiency to examine the effect of technology improvements on bank financial performance. Lastly, banks' managers maximise the profits of their investments by pursuing the highest returns for what they deem to be satisfactory levels of risk. Thus, considering bank risk management alongside profitability and efficiency in future works could provide more comprehensive measures of banking performance and support banks and policymakers with recommendations for a more profitable, efficient, and stable banking sector.

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Appendices

Appendix A (Algorithm 2):

Step 1: Using the original data of outputs, Y_{it}, and inputs, X_{it}, (that are all positive) compute DEA efficiency score $\widehat{\delta}_i$.

Step 2: Use the method of maximum likelihood to obtain an estimate $\hat{\beta}$ of β as well as an estimate $\widehat{\sigma_\varepsilon}$ of σ_ε in the truncated regression of $\widehat{\delta}_i$ on z_i using $m < n$ observations where $\widehat{\delta}_i > 1$.

Step 3: Loop over the next four steps **([3.1]- [3.4])** 100 times to obtain a set of bootstrap estimates.

$$A = \left\{ \left(\widehat{\beta^*}, \widehat{\sigma_\varepsilon^*}\right)_b \right\}_{b=1}^{100}:$$

[3.1] For each $i=1..., m$, draw ε_i from the $N\ (0, \widehat{\sigma^2}_\varepsilon)$ distribution with left-truncation at $(1 - z_i\ \hat{\beta})$.

[3.2] Again for each $i=1..., n$, compute $\delta_i^* = z_i\ \hat{\beta} + \varepsilon_i$.

[3.3] Set $x_i^* = x_i$, $y_i^* = y_i\ (\widehat{\delta}_i / \delta_i^*)$ for all $i=1,2...n$.

[3.4] Compute the new technical efficiency $\widehat{\delta^*}_i$ by replacing $Y^* = [\ y_1^*,..., y_n^*\ ]$, $X^* = [\ x_1^*,..., x_n^*\ ]$.

Step 4: For each $i=1..., n$, compute the bias corrected estimator $\hat{\widehat{\delta}}_i$ using bootstrap estimates in **Step 3.4** and the original $\widehat{\delta}_i$.

Step 5: Use the maximum likelihood method to estimate the truncated regression of $\hat{\widehat{\delta}}_i$ on z_i, yielding estimates $\hat{\hat{\beta}}$, $\hat{\hat{\sigma}}$.

Step 6: Loop over the next three steps **([6.1]- [6.3])** 2000 times to obtain a set of bootstrap estimates.

$$K = \left\{ \left(\widehat{\beta^*}, \widehat{\sigma^*}\right)_b \right\}_{b=1}^{2000}:$$

[6.1] For each $i=1..., n$, draw ε_i from the $N\ (0, \hat{\hat{\sigma}})$ distribution with left-truncation at $(1 - z_i\ \hat{\hat{\beta}})$.

[6.2] Again for each $i=1..., m$, compute $\delta_i^{**} = z_i\ \hat{\hat{\beta}} + \varepsilon_i$

[6.3] Use the maximum likelihood method to estimate the truncated regression of δ_i^{**} on z_i, yielding estimates $\hat{\hat{\beta}}^*$, $\hat{\hat{\sigma}}^*$.

Step 7: Use bootstrap values in **K (Step 6)** and the original estimates $\hat{\hat{\beta}}$, $\hat{\hat{\sigma}}$ to construct $(1-\alpha)$ estimated confidence intervals for each element of β, σ_ε..