



UNIVERSITY OF PIRAEUS

DEPARTMENT OF BANKING AND FINANCIAL MANAGEMENT

Essays on Risk Management

*A Thesis submitted in fulfilment of the requirements for the Degree of
Doctor of Philosophy*

Author
Paraskevas Zaverdinos

Supervisor
Gikas Hardouvelis
Professor

January 24th , 2025

*To my wife Aiki who
has always been my pillar of strength*

Acknowledgements

I would like to express my gratitude to my supervisor, Professor Gikas Hardouvelis, for his continuous support and mentorship during this long journey. Not only he was able to guide me to the right direction when choosing research topics but also provided concrete and valuable feedback in our meetings that always enabled me to further progress with my research. In addition, I would like to thank the professor for his patience and true understanding of the fact that simultaneously to my PhD studies, I have also been a young professional.

I would also like to thank all faculty members of the Banking and Financial Management department for their valuable comments during my Doctoral Seminar presentations. In particular, I would like to thank professor Nikolaos Kourogenis and Professor Nikolaos Egglezos for entering my doctoral advisory committee and also express my appreciation to the former director of the PhD program, Professor Michalis Anthropolos, who devoted so much of his time to organise the academic and doctoral seminar series. My appreciation also goes to the President of the department, Professor Seraina Anagnostopoulou, for her continuous efforts to provide the highest possible academic standards to all students and faculty members of the department. Outside of the University of Piraeus, I would like to express my gratitude to professor Panagiotis Samartzis for both his comments and for the time he devoted to critically assess this research.

Furthermore, special thanks to my good friend and fellow PhD student George Samartzis who co-travelled with me from the very beginning and provided encouragement during this journey.

Finally, I would like to thank my family and especially my wife Aiki, for the constant and unconditional support throughout this period. Without this support, the completion of the PhD would have been impossible.

Table of Contents

Introduction	5
1. Chapter I: The effect of the Bank's risk profile on Capital Adequacy Buffers and their Cyclical behaviour	12
1.1 Literature Review	13
1.2 The dataset	16
1.3 Empirical Model	17
1.4 Empirical results	24
1.4.1 Spanish Banks during Period 1988-2000	24
1.4.2 Spanish Banks during Period 2001-2018	27
1.4.3 All European Banks during Period 1988-2018	29
1.4.4 Model Robustness	30
1.5 Policy Implications	31
2. Chapter II: The impact of Reversal Interest Rate on Bank's Profitability, Risk Taking, Leverage and Bank Activity	35
2.1 Literature Review	36
2.2 The theory behind Reversal Interest Rate	40
2.3 Creeping-up Effect	45
2.4 The dataset	45
2.5 Empirical Model	47
2.6 Empirical Results	50
2.6.1 Propensity Score Matching	50
2.6.2 NIRP effect on Bank Operations	54
2.6.3 NIRP effect on Risk Appetite & Riskiness	57
2.6.4 NIRP effect Capital Adequacy	60
2.6.5 NIRP effect on Profitability	62
2.6.6 Effect of Rate Changes	64
2.6.7 Empirical Evidence of the Creeping-up effect	65
2.6.8 Optimal Sequencing of QE	68
2.6.9 Robustness Checks	73

3. Chapter III: The effect of capital ratios on the probability of a Banking crisis and the associated Economic cost	76
3.1 Literature Review	77
3.2 Empirical Model	78
3.2.1 Assessing the impact of capital adequacy ratios on the probability of crisis	78
3.2.2 The dataset	79
3.2.3 Empirical results	81
3.3 Empirical Model	84
3.3.1 Evaluating the Economic cost of increased capital adequacy ratios	84
3.3.2 Crisis Aftermath: Economic policies that speed up Economic recovery	88
4. Conclusions	92
5. Appendix	95
6. References	99

Introduction

The outbreak of the Global financial meltdown in 2008-2009 was probably the most severe economic turbulence the world economy has faced since Great Depression, bringing both financial markets and also the global banking system under severe stress. The extent of the crisis resulted in both financial intermediaries but also central banks to fundamentally revise the way they operated. Up until this point central banks used changes in the short-term policy rates as the main tool in order to achieve their macroeconomic goals and stabilize prices. The remaining “conventional monetary policies” included

a) Open Market operations aiming to provide liquidity to banks for one week (called Main Refinancing Operations, or MROs) or three-months (called Longer-Term Refinancing Operations, or LTROs)

b) Minimum reserve requirements which in essence is a percentage of the bank’s balance sheet , required to be deposited with the national Central Bank and

c) Marginal lending and deposit facilities provided by central banks which allow institutions to access overnight liquidity or make overnight deposits respectively.

Very quickly the major Central banks exhausted these conventional monetary policies and relied to unconventional monetary policies to further stimulate their economies which were hit by low growth and low inflation rates. The ECB for example among others introduced the following three most notable unconventional policies in historical order: Firstly, during the summer of 2012, ECB announced the initiation of the OMT (Outright Monetary Transactions) program that allowed ECB to perform “outright purchases” of sovereign bonds in the secondary market, overcoming scepticism (mainly from Germany) that such a decision violates Article 125 and Article 123 of the Maastricht treaty related to restrictions on both bail-out and monetary financing rules. The OMT intervention via SSM, resulted in an immediate decrease of sovereign yields for most of the euro area countries (Altavilla et al, 2016) and partially relieved the pressure on the financial intermediates of these countries allowing them to increase lending. Secondly, during summer 2014, ECB reduced policy rates (specifically the deposit rate under the ECB’s deposit facility) to negative region for the first time. While theoretically reduction of policy rates has a direct positive effect on the level of Lending, reality showed that financial intermediaries were hesitant to transfer negative rates to the depositors and preferred to decrease their lending margins instead. This strategy motivated the fundamental question of how effective is such a Negative Interest Rate Policy (NIRP) and in general whether there is a lower bound on central banks’ monetary policies. Thirdly, during spring 2016 ECB introduced the CSPP program (i.e Corporate Sector Purchase Program) that allowed ECB to perform large transaction on Corporate Bonds of large euro area firms. Almost immediately after the announcement, yields of corporations whose bonds were eligible for purchase dropped significantly. In the medium-term, bank loans of these firms were gradually replaced by cheaper bond debt which in turn resulted in a release of new bank funds to smaller companies (Benjamin Grosse – Rueschkamp et al, 2019).

An important aftermath of the crisis is the realization of the central role of financial intermediaries' robustness in order to support the transmission of monetary policy and that there are additional components that affect the so-called traditional lending channel that we previously paid limited attention. Especially up until the crisis there was limited research on the interlink between central bank policy, bank capital requirements and riskiness of financial institutions balance sheets. Specifically, according to the traditional transmission mechanism of monetary policy as expressed by Bernanke et al (1995) the credit channel contains the "bank lending channel" and the "balance sheet channel". Any change in the monetary policy would impact both channels and will eventually show its effect on lending. The lending channel theory that we are mostly interested here, first introduced by Bernanke et al in 1988 and 1992, supports that any contractionary monetary policy imposed by central banks will lead to a drainage in institutions deposits which will eventually reduce supply of loans. In essence, according to the traditional bank lending theory the driving force of the bank lending supply are the movements on the Liability side of the balance sheet caused by monetary policy changes. For completeness the balance sheet channel argues that during periods of contractionary monetary policy, financial intermediaries would redirect credit supply away from smaller companies and towards larger companies under the assumption that smaller companies are riskier compared to the larger ones.

Another aftermath of the crisis is the realization of the importance of having procyclical in nature capital regulations. These are capital regulations that promote increasing capital requirements and capital buffers (i.e buffers in excess of the requirements) during times of economic upturn that can then be consumed during times of economic downturn. The idea was first introduced by Berger, 1995 who argued that financial institutions ought to keep capital buffers for two main reasons a) in order to use it as a shield for unexpected shocks and b) to be able to benefit from unexpected investment opportunities that may arise. To address this point, Basel III framework which was designed as a response to

the recent financial crisis introduced an additional “countercyclical buffer” which forces institutions to accumulate capital during periods of rapid expansion that are usually associated with increasing systemic risks. This motivated the fundamental question of whether capital adequacy regulations are indeed procyclical and whether banks follow a forward-looking approach on capital buffers i.e whether the financial institutions will try to increase their capital buffers during periods they expect to undertake higher risks in their balance sheets.

The current research is split into three chapters. The first Chapter was motivated from the discussion around cyclicity of capital requirements and if banks have a proactive and forward-looking approach on the capital buffers they decide to keep. Our work follows the methodology introduced by Ayuso et al , 2002 for assessing the cyclicity of buffers the Spanish banks hold. The work from Ayuso et al is quite monumental in the capital management space as it triggered the introduction of the “countercyclical buffer” in the Basel regulation. According to Ayuso et al, capital buffers show a significant negative relationship with the business cycle, specifically a 1% growth in GDP reduces capital buffers by approximately 17%. The above result motivated the BCBS committee to impose the countercyclical buffer where banks are obliged to hold additional capital (as part of Pillar I requirements) during economic expansion. That way banks are asked to accumulate sufficient capital during the expansion cycle that can be used as a cushion during periods of economic recession and hence avoid having to substantially increase capital (and as a consequence reduce lending activity through an increased lending spread) during the recession cycle. In addition, up until Ayuso et al, published their work most researches focused on whether Capital requirements are cyclical, disregarding that it is unlikely for banks to keep just the regulatory required capital. Expectation is that the majority of banks hold buffers which most of the times are quite sizeable.

In contrast with Ayuso et al, our work is not only limited to Spanish Banks and just the period when Basel I was applicable, but extends to 697 banks across Europe from 1987 to 2018. In essence we take into account the periods when the Balel II & II.5 frameworks were applicable with respect to the calculation of Capital Adequacy ratios. Our work is quite innovative for another reason too as it tries to answer the question of whether management of the institutions have a forward-looking approach with respect to the institution's capital buffers during periods of increasing risk in their balance sheets. Specifically, while Ayuso et al were able to identify the negative correlation between capital buffers and the business cycle for a group of Spanish Banks, their research was not able to adequately explain why cost of failures showed a negative sign. The authors in their theoretical model prove that the sign of NPLs should have been positive but justify the negative sign of their empirical model on the basis that NPLs are measured ex-post (and therefore refer to loans that have been granted many years earlier). In reality someone would have expected that when banks expect increased NPLs (and therefore risks) in their balance sheets they would have increased their capital buffers to avoid bankruptcy

To address the above misalignment, we have included the Risk Weighted Asset density as a far better proxy for the risk profile of the banks compared to Non-performing Loans that was widely used in earlier researches. The main advantage of Risk Weighted Assets variable is that it captures all three main risks a bank is facing (i.e Credit, Market and Operational Risk) compared to NPLs which act as a proxy for Credit Risk only and can only be representative for smaller retail and commercial banks. In general, NPLs can be misleading for larger complex institutions that may have investment banking or large trading floors. In this context, we believe that, there is an additional policy implication as the RWA density should be part of the indicators used to determine and rank GSIBs (Global Systemically Important Banks) on the basis that the current approach where only Asset size and Complexity of the balance sheet is used does not take into account the true riskiness of the institution. A

large institution may have a very big asset size but may have smaller relative risk in its balance sheet, whereas a medium size institution (in terms of balance sheet size) may have a very large risk exposure which implies that it may require an additional capital buffer.

The second chapter is motivated by one of the unconventional policies followed by Central banks during the recent financial crisis that of the reduction of the policy rates to negative territories for long periods. Such approach became standard practise for a number of Central Banks of the crisis period such as the ECB, Swedish Risk Bank, the Japanese Central Bank and the Swiss Central Bank. Our research is based on the “Reversal Interest Rate theory” introduced by Markus Brunnermeier et al, AER, 2023. According to this theory there exist a lower bound of monetary policy which is called the “Reversal Interest Rate”, where any further rate cut imposed by the Central bank will “reverse” its effect and will become contractionary for lending. That is happening because of the existence of two opposite forces affecting the institution’s net worth. The first force that is positively affected by a rate cut is capital gains especially for long term fixed rate assets. The second force (opposite to the first one), is the bank’s Net-Interest Income which decreases when the rates go lower. At the point when a reduction in Net-interest income becomes greater than the increase in capital gains, monetary policy hits the lower bound and decreases loan supply of the institution.

The main contribution of this research is the empirical assessment of the Reversal interest rate theory and whether it really exist. We have used a large dataset of Banks and we have applied a DiD methodology. We have tested the impact of NIRPs on Profitability, Riskiness, Capital Adequacy and of course Bank operation such as Lending. We have also examined the existence of the Creeping-up effect and assessed the optimal sequence for doing Quantitative Easing, which is another type of unconventional monetary policy.

Finally, the third Chapter is motivated from the role of financial institutions during the transmission of monetary policy as expressed in the Lending channel

theory and tries to answer a set of interlinked questions. The first question we are trying to answer is the effect of capital adequacy ratios on the probability of a banking crisis. To address this, a multivariate logit model was used where the likelihood of a financial crisis is a function of a matrix of potential explanatory variables both macroeconomic and bank specific. The period we have run our empirical results is from 1988-2016 and include Banking Crisis for more than 70 countries. The second question we are trying to examine is the impact of capital adequacy regulations in the Economic Output and overall Credit provided by Banks. To evaluate this, we made the assumption that any regulatory capital requirement or any bank decision to increase the capital adequacy ratios is going to impose cost to the economy as the financial intermediaries will attempt to transfer to the clients an elevated cost of funding through the mechanism of an increasing Lending Spread. Our evaluation was based on simultaneously estimating a system of regression models using an SUR (Seemingly Unrelated Regressions) methodology. The third question is related to identifying those Economic policies that are more effective to accelerate Economic recovery. The most important policies that were examined are a) the effect of increased Bank Credit to the Private Sector b) Labor Changes c) Tightening of the Fiscal Balance by the government d) Policies against inflation e) and policies targeting household consumption and f) Investments. The aforementioned economic policies were assessed against number of years it took for the Economy to reach the pre-crisis level in order to identify the most effective one.

Chapter I: The effect of the Bank's risk profile on Capital Adequacy Buffers and their Cyclical behaviour

Abstract

We evaluate the interlink of the business cycle and Risk Profile of European banks against the regulatory capital adequacy buffers. Based on the empirical results of our estimated theoretical model we find that Capital buffers have a negative correlation with the business cycle and that banks expecting to have riskier profile in future tend to hold higher capital buffers. We find that NPLs which is used as a proxy for the Risk Profile of Banks by most researchers is not robust. Therefore, we propose the use of RWA density indicator as a variable that better captures the Risk appetite of Banks. Given that RWA by construction is in the denominator of Capital Adequacy Ratios, the fact that we see a positive relationship is very strong evidence of the forward-looking approach followed by Banks. This result is a strong argument that the Basel III “countercyclical buffer” is not really needed given banks will increase capital buffers on their own when they expect an increase in the risk of their balance sheets.

1.1 Literature Review

The Basel Committee on Banking Supervision (BCBS) accords

BIS (Bank for International Settlements) introduced in 1988 the first ever Basel Accord (known as Basel I). That was the first attempt to agree global risk-based standards for the Capital Adequacy of the financial institutions. The most significant innovation was undoubtedly the introduction of Cooke Ratio (named after Peter Cooke, Bank of England) which is the ancestor of the Bank's Total Risk Weighted Assets. The Cooke Ratio only applied on Credit risk Exposures and was a simple weighting and aggregation of the credit exposures with a prescribed Risk Weight.

The 1996 Basel Amendment (implemented in 1998), known as "BIS 98", introduces for the first time Risk Weighted Assets for Market Risk through the calculation of Value-at-Risk.

In 2004 Basel introduces a new set of requirements known as Basel II. The new standards which were implemented by banks in 2007, just before the recent global financial crisis, introduce three pillars (Supervisory Review, Minimum Capital Requirements, and Market Discipline). Specifically, for Credit Risk, Basel II allows financial institutions to choose from three approaches to calculate their Credit RWA (the Advanced IRB Approach, the Foundation Internal Ratings Approach and the Standardized Approach).

During the financial Crisis, the committee revised the Basel II standards and introduced what is known as Basel II.5 which became effective from 2012. The most important innovation compared to Basel II was the introduction of stress VaR (SVAR), Comprehensive Risk Measure (CRM) and Incremental Risk Charge (IRC).

In December 2010, Basel Committee introduced Basel III. The main goal of Basel III was to further increase capital requirements and put a limit on the

amount of Leverage the Financial Institutions can have on their balance sheets. Some other innovations include among other the introduction of the Countercyclical Buffer and the Capital Conservation buffer. Basel III was implemented in phases from 2013 to 2023. Currently, the BCBS committee is preparing a new and stricter set of Basel requirements (called BaselIV) which will be implemented in phases over the decade.

Literature around Capital buffers

There have been several studies trying to explain why banks hold excess capital. Jackson, 1999 believes that financial institutions hold excess capital as a sign of soundness to the market and the Rating agencies. Milne, 2004 believes that banks are special type of corporations where their assets cannot be sold at the full present value and there are significant costs whenever raising new shareholder capital. Because of these market inefficiencies the bank retains larger amount of earnings whenever it's falls below a desired buffer. That way banks reduce the incidence of costly liquidations or/and recapitalizations. Milne et al, 2001 believe that excess capital buffers act as an insurance against unnecessary costs generated from intervention of the supervisory authority following requirement violation.

Marcus, 1984 believes that the existence of 'franchise value' in essence a series of future cash flows with a positive net present value provide shareholders an incentive to avoid liquidation, by excess capital buffers and decreasing bank assets' riskiness. Hence Franchise value limits moral hazard in banks.

Estrella, 2004 examined the cyclicity of VaR based capital requirements. A financial institution faces three main types of costs: the failure cost, the holding capital cost and the cost related to changes in external capital. Estrella hypothesis assume that the objective of the bank is to minimize all three main

types of costs over infinity. According to Estrella a minimum capital requirement based on VaR, is likely to be procyclical.

Ayuso et al, 2004 reviewed the relation between business cycle and capital buffers for Spanish banks. In their study they first provide a theoretical model, based on Estrella's hypothesis, that explains the determinants of capital buffers which upon estimation shows a significant negative relationship between capital buffers and the business cycle. This research has been a milestone in the discussion for the introduction of a countercyclical buffer in the Basel regulation.

Jokipii et al, 2008 re-estimated the empirical results of the model introduced by Ayuso et al using a larger sample of banks across more countries and found that commercial, savings and large banks, show negative correlation with the business cycle. On the other hand, cooperative and smaller banks exhibit positive co-movement.

Stolz et al, 2011 re-estimated the empirical results of the model introduced by Ayuso et al using German banks only. They found that German Banks' capital buffers move countercyclically with the business cycle. Savings banks were found to have stronger fluctuation than cooperative banks due to larger fluctuation of RWAs in saving banks. Interestingly, during a business cycle downturn Low-capitalization banks don't reduce RWAs (i.e increase Capital Ratios) as much as their well-capitalized peers.

Brei et al, 2014 extend Ayuso's empirical model to take into account the effects during crisis. In their research, capital adequacy ratios seem to fluctuate more procyclical and less countercyclical during the crisis period.

1.2 The data set

We have created an incomplete structure of panel data. Our dataset includes a total of 4313 Banks worldwide. Out of those we focused on Europe and specifically we isolated 697 banks coming from 24 European countries. Our data spans from 1987 until 2018 and include Balance Sheet Components (eg Total Loans, Total Assets) and Capital Adequacy metrics (Capital Adequacy Ratio, Tier I capital, Tier II capital etc). We used, among others, the FT Banker Database , Bloomberg and The Global Economy as main sources to collect our data. We have further enriched our database with Macroeconomic data from 191 countries including all European countries.

Table 1.1

Number of Banks in our dataset by country

Number of European Banks per Country	
Andorra	3
Austria	32
Belgium	14
Cyprus	12
Denmark	16
FaroeIslands	2
Finland	8
France	25
Germany	58
Greece	7
Iceland	5
Ireland	13
Italy	65
Liechtenstein	3
Luxembourg	24
Malta	12
Netherlands	26
Norway	16
Portugal	22
Spain	30
Sweden	9
Switzerland	80
Turkey	38
UK	176

Notes: This table shows the number of banks by country in our sample. Our data spans from 1987 until 2018 and include Balance Sheet Components and Capital Adequacy metrics.

1.3 Ayuso's model and Empirical equation

The formation of the model introduced by Ayuso starts from the below simple equation which is standard in the literature

$$K_t = K_{t-1} + I_t$$

Where K_t : Is the end of period t capital

And I_t : are issues of stocks and repurchases

For completeness we mention that Estrella (2004) includes net income (profit or losses) separately as an additional factor in his model. As recommended by Estrella (2004) the decision of how much capital a bank should hold depends on three different and competing types of costs

Initially, holding capital is considered a direct cost for financial institutions which needs to be remunerated. Per Campbell (1979), holding capital is costlier than other liability types such as debt or deposits.

Secondly holding capital reduces another type of cost called failure costs which include bankruptcy costs, legal and reputational costs (Acharya 1996)

Finally, any change in the capital levels requires adjustment costs that can be either pure transaction costs but also the costs related to asymmetric information between buyers and issuers. Specifically, buyers see the issues of new capital as a signal of mispricing and that the current market prices are greater compared to the true share value and hence reason the issuer selected this time to issue new stocks. As a result, buyers will require higher compensation to enter the desired adjustment. Myers et al (1984), Winter (1994), McNally (1999)

According to Ayuso et al (2004) and given the above, a representative bank will minimise the intertemporal cost by trying to solve the below minimisation problem

$$\text{Min}_{\{I_{t+i}\}_0^\infty} E_t \sum_{i=0}^{\infty} \beta^i C_{t+i} \quad (1)$$

Such that

$$C_t = (a_t - \gamma_t)K_t + \left(\frac{1}{2}\right) \delta_t I_t^2 \quad (2)$$

$$K_t = K_{t-1} + I_t \quad (3)$$

Where α is the cost for remunerating capital, γ are the failure costs and δ are all the adjustment costs described earlier.

We solve this by substituting (3) in (2)

$$\Rightarrow C_t = (a_t - \gamma_t)(K_{t-1} + I_t) + \left(\frac{1}{2}\right) \delta_t I_t^2$$

and taking the First order condition, we end up

$$I_t = E_t \left(\frac{1}{\delta_t} \sum_{i=0}^{\infty} \beta^i (\gamma_{t+i} - a_{t+i}) \right) \quad (4)$$

Taking expectations on (3) and substituting (4) we get

$$\Rightarrow E_t(K_t) = K_{t-1} + E_t \left(\frac{1}{\delta_t} \sum_{i=0}^{\infty} \beta^i (\gamma_{t+i} - a_{t+i}) \right) \quad (5)$$

Let's assume now that there is some minimum capital requirement denoted as K^* . If we subtract K^* from both sides of equation (5), rearrange and replace expectations with the actual capital at the end of period t we get the below:

$$(K - K^*)_t = \underbrace{(K - K^*)_{t-1}} + \underbrace{\left(\frac{1}{\delta_t} \sum_{i=0}^{\infty} \beta^i (\gamma_{t+i}) \right)} - \underbrace{\left(\frac{1}{\delta_t} \sum_{i=0}^{\infty} \beta^i (a_{t+i}) \right)} + \varepsilon_t$$

(6)

Equation (6) implies the factors we need to control in our empirical model

The first regressor should be the dependent variable lag capturing the adjustment costs and expected to have a positive sign. The second set of regressors should capture the banks failure costs (γ) which are connected to a) the bank's size and too big to fail hypothesis and b) to the risk appetite of the bank. Expectation for these variables is to have a positive sign. Finally, the third

set of regressors should capture any remunerating capital cost and expected to have negative sign.

The proxies we have used to estimate equation (6) can be seen in the below empirical equation:

$$BUF_{it} = \beta_0 BUF_{it-1} + \beta_1 ROE_{it} + \beta_2 NPL_{it} + \beta_3 BIG_{it} + \beta_4 SMA_{it} + \beta_5 GDPG_t + \beta_6 BASEL_t + \eta_i + \varepsilon_{it} \quad (7)$$

Table 1.2:

Factors included in the model and expected signage

Types of costs	Variables	Expected sign	Literature
Adjustment Costs	BUF_{it-1}	(+) Positive	Myers and Majluf (1984), Winter (1994), McNally (1999)
Cost of Failure (includes Risk Appetite and Size of institution)	NPL_{it} BIG_{it} SMA_{it}	(+) Positive for NPL, SMA (-) Negative for BIG	Keeley (1990), Salas and Saurina (2002), Myers and Majluf (1984), Winter (1994)
Costs for Remunerating Capital	ROE_{it}	(-) Negative	Campbell (1979) and Myers and Majluf (1984)

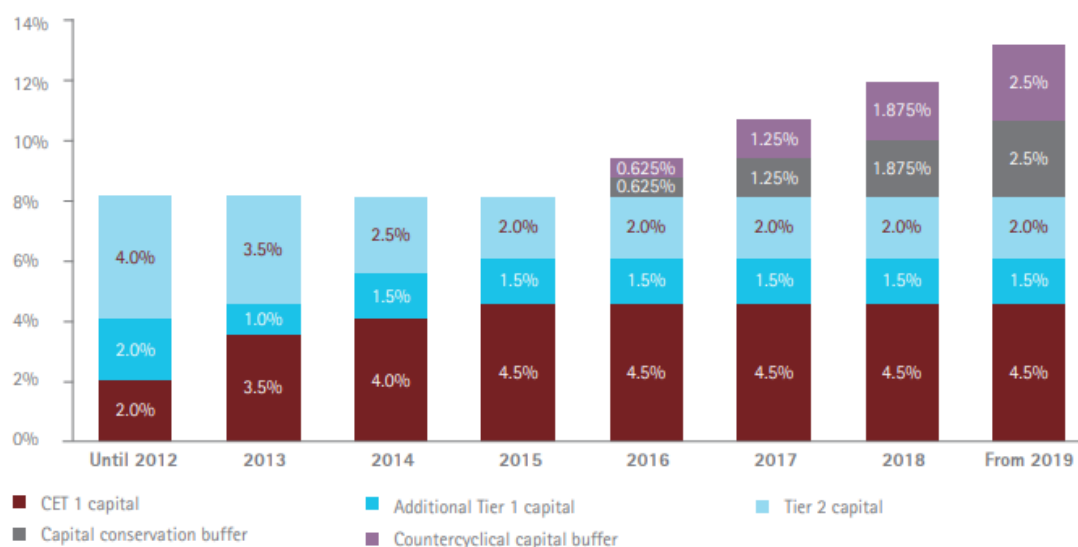
Notes: This table shows the three main costs that a bank tries to minimize. The first regressor should be the dependent variable lag capturing the adjustment costs and expected to have a positive sign. The second set of regressors should capture the banks failure costs which are expected to have a positive sign. Finally, the third set of regressors should capture any remunerating capital cost and expected to have negative sign

In addition to the regressors implied by the model we have also added two additional variables a) $GDPG$ which captures the growth on GDP and is added in the model to determine if the business cycle affects capital buffer held by the institutions and b) $BASEL$ which is a dummy variable to control for all the

changes imposed by BCBS after the introduction of BASEL III in phases from 2016 and onwards. Basel III has not only changed the minimum regulatory capital (figure 1.3) but also its composition and the methodology it was measured so far.

Figure 1.3:

Evolution of minimum Pillar I Capital requirement according to Basel III – Source: Accenture Basel III handbook



Notes: This figure shows the minimum Capital requirements under Basel III Pillar I and their composition. When calculating the capital buffers for every bank the Pillar I thresholds of every country have been used to demonstrate the minimum capital requirement

As described earlier the work from Ayuso et al, 2004 triggered the introduction of the countercyclical buffer in the Basel regulation. Following, their theoretical model the authors had to include proxies for all three type of costs described earlier (i.e Adjustment costs, Failure costs and costs for Renumerating capital). While Ayuso et al were able to identify the negative correlation between capital buffers and the business cycle for a group of Spanish Banks, their research was not able to adequately explain why cost of failures showed a negative sign. The authors in their theoretical model prove that the sign of NPLs should be positive but justify the negative sign of their empirical

model on the basis that NPLs are measured ex-post (and therefore refer to loans that have been granted many years earlier). In reality someone would have expected that when banks expect increased NPLs (and therefore risks) in their balance sheets they would increase their capital buffers to avoid bankruptcy.

The contribution of this chapter of our research is that A) we have explored ways of correcting this misalignment by using Risk Weighted Assets as a better proxy for the risk profile/appetite of banks. We believe that NPLs that have been used widely in literature as proxy for the risk profile of banks is only applicable for certain type of banks such as smaller retail/commercial banks and would be misleading for larger complex institutions that could also have investment banking and/or large trading floors. To our current knowledge we are the first to use the RWAs in this type of research. B) We have explored whether the negative relationship between the business cycle and capital buffers also holds for European Banks and for a more extended period to the one reviewed by Ayuso et al. C) We have identified Profits as an additional factor that explain the move in the Capital buffers and must be included in our empirical model

Overview of Risk Weighted Assets (RWAs) and the RWA density indicator

Total Risk Weighted Assets (RWAs) are split in three components (Market RWA, Credit RWA and Operational RWA) as can be seen in equation (8)

$$Total\ RWA = Market\ RWA + Credit\ RWA + Operational\ RWA \quad (8)$$

Specifically for Market Risk RWA,

$$Market\ RWA = (m + b) \max(VaR, \overline{VaR}_{60days}) + \\ (m + b) \max(StressedVaR, Stressed\overline{VaR}_{60days}) + \\ \max(IRC, \overline{IRC}_{12weeks} + \max(CRM, floor) + SC \quad (9)$$

Where

VaR: is the standard 10day VaR at 99%

Stressed VaR: is the 10day VaR at 99% calibrated to financial crisis data during 2008-2009

IRC: is the incremental risk charge for migration and default risk of non-securitised products

CRM: is the incremental charge for correlation trading portfolios (CDOs, MBS etc)

Floor: is α times capital charge for specific risk where $\alpha= 8\%$

SC: is the standardised calculation charge on securitised exposures (not captured by CRM)

m: is a model-based multiplier, $m \geq 3$

b: is multiplier based on the VaR/SVaR breaches

For Credit Risk RWA,

Credit RWA =

$$= \left\{ \underbrace{LGD \Phi \left(\frac{\Phi^{-1}(PD) + \sqrt{\rho} \Phi^{-1}(0.999)}{\sqrt{1-\rho}} \right)}_{\text{Expected losses}} - \underbrace{LGD PD}_{\text{Expected losses}} \right\} \times MA \times SF \times MCR \times EAD$$

(10)

LGD: loss given Default

PD: probability of default of the counterparty

MA: maturity adjustment applied relevant to maturities over 1 year

SF: Basel scaling factor equal to 1.06

MCR: Minimum Capital Required = 1/(% of Capital Required)

Looking closer at the Credit RWA formula we define WCDR as the Gaussian copula that provides the worst case default rate given a confidence level of 99.9%

$$WCDR_i = \Phi \left(\frac{\Phi^{-1}(PD_i) + \sqrt{\rho}\Phi^{-1}(0.999)}{\sqrt{1-\rho}} \right)$$

The Basel text assumes that all the obligors of a bank have the same pairwise correlation ρ

For Operational RWA

For every business line Gross Income (G.I.) is an indicator that represents the magnitude of business operations and hence the possible size of operational risk for each of the business lines. The Operational Risk Weighted Assets for every business line is computed from the multiplication of G.I with a coefficient (called β) attributed to the specific business line.

$$K_{TSA} = \frac{\sum_{years 1-3} \max(\sum(GI_{1-8} \times \beta_{1-8}), 0)}{3} \quad (11)$$

Table 1.4:

BCBS operational RWA beta coefficients. Source BCBS

Values of betas		
	Business lines	Beta factors
β_1	Corporate finance	18%
β_2	Trading and sales	18%
β_3	Retail banking	12%
β_4	Commercial banking	15%
β_5	Payment and settlement	18%
β_6	Agency services	15%
β_7	Asset management	12%
β_8	Retail brokerage	12%

Notes: This table shows the BCBS operational RWA beta coefficients. The Operational Risk Weighted Assets for every business line is computed from the multiplication of Gross Income with a β coefficient attributed to the specific business line

RWA density is equation (8) divided by Total Assets and represents the percentage of Total assets that are deemed risky. RWA density therefore is a measure of riskiness of assets and the YoY movement of the ratio implies a change in the risk profile and risk appetite of the bank's Assets.

$$RWA\ Density = \frac{Market\ RWA + Credit\ RWA + Operational\ RWA}{Total\ Assets} \quad (12)$$

Per the usual practice with Panel Data we estimated the equation using the Generalised Method of Moments (GMM), which as the name suggests is a generalization of the classical Method of Moments (MM). In the **Appendix** we provide an overview of both the Method of Moments and the Generalised Method of Moments.

1.4 Empirical Results

1.4.1 Spanish Banks During Period 1988-2000

Similar to the approach followed by Ayuso et al (2004) we transformed the empirical equation into differences in order to obtain unbiased estimators through the GMM. We chose the NPL and ROE as endogenous variables whereas the variables for size (BIG, SMALL) and business cycle were considered as exogenous. That way we remained consistent with the hypothesis of Ayuso et al but also, we avoided correlation with the error term, which could have caused endogeneity. Table 1.5 shows both the results of our GMM and

Pooled OLS estimation for Spanish Banks only, in comparison with the ones estimated by Ayuso for similar time period (1988-2000).

Table 1.5:

Model Estimation for Spanish Banks for the period 1988-2000. Comparison versus results presented by Ayuso et al

Variable	Ayuso Model1	Model1 Replication GMM	Model1 Replication OLS
Sample	142 banks	12 banks	12 banks
BUFi,t-1	0.40 (0.00)	0.24 (0.01)	0.69 (0.00)
ROEi,t	-0.43 (0.01)	-1.34 (0.00)	-0.14 (0.79)
NPLi,t	-1.99 (0.00)	-2.13 (0.00)	-1.35 (0.50)
BIGi,t	-14.06 (0.15)	-34.87 (0.24)	-5.78 (0.23)
SMAi,t	21.74 (0.12)	18.82 (0.05)	18.50 (0.04)
GDPGt	-4.09 (0.00)	-7.36 (0.00)	-5.81 (0.06)
<hr/>			
m1	-4.65 (0.00)	0.16 (0.17)	adjR ² =78.41%
m2	0.16 (0.87)	-0.32 (0.74)	DW= 1.56
Sargan Test ¹	114.15 (0.26)	4.40 (0.62)	

Notes: The variables used in the estimation of the model are the following: BUF: capital buffer as proxy for adjustment costs; ROE: return on equity as a proxy for remuneration costs; NPLs: non-performing loans as a proxy for failure costs; BIG: dummy variable reflecting banks in the highest decile by Asset size; SMA: dummy variable reflecting banks in the lowest decile; GDPG: GDP Growth. Dependent variable is BUF, p-values in brackets

We can see that in both our GMM and Pooled OLS models there exist a statistically strong negative relationship at 1% between GDP growth and Capital buffer size which is an evidence of cyclicity of the buffer. Similar result has been presented by Ayuso et al. This result implies that institutions tend to decrease their capital buffer they hold during upturns of the economy and increase it during downturns. Ayuso believes that this is happening because

¹ Sargan's H0 hypothesis is that instruments are not correlated with residuals. We usually do not want to reject H0 when we use the Sargan Test. In case H0 is rejected we will need to reexamine the instruments that were selected

institutions or their risk models tend to underestimate risk during upturns something that requires actions from the regulators under both Pillar I and Pillar II. While the obvious action under Pillar I is to impose a higher capital buffer under upturns the Pillar II action involves the closer and strict monitoring of the banks' behaviours during the expansionary stage of the cycles. This combination could potentially prevent negative solvency effects during a sudden cyclical correction.

The remaining coefficient signs are similar to the ones found by Ayuso et al, however we can see that NPLs and ROE are not statistically significant when we use the Polled OLS estimation methodology. Specifically, for NPLs the sign is opposite to what indicated by the theoretical model. The two dummy variables (BIG, SMA) capturing the size of the institution come with the expected sign in line with the literature and the too-big-to-fail hypothesis. As we can see in all models, smaller institutions tend to keep significantly higher capital buffers as they know that they will face substantially more difficulties in raising capital during an economic downturn compared to a larger competitor. In addition to this, it is more probable for a regulator to allow a smaller non-systemic bank to collapse compared to a larger firm that can cause a domino effect in the economy. On the other hand, larger institutions tend to keep smaller capital buffers relying on their systemic nature and try to optimize their revenues over capital buffers.

Interestingly the sign of the NPL which is used as a proxy for the risk appetite of the banks is negative in all models which is opposite to the theoretical model. Ayuso et al explain this deviation from the theoretical model due to NPLs being an ex post measurement. Our expectation is that if management of the institution expects the NPLs to grow in the future it would try to increase the capital buffer of the institution so that it can absorb the losses and minimize the probability of default. In addition to this we can see that although the negative coefficient of the NPLs is statistically significant under GMM, this is not the case when we use the Polled OLS estimation methodology.

1.4.2 Spanish Banks during Period 2001-2018

One of the goals of this study is to investigate if the above relationships hold in the subsequent period 2001-2018 which is not captured by Ayuso et al. We rerun our empirical results for the subsequent period 2001-2018 and we included 24 Spanish banks. Table 1.6 provides a comparative view of all results across both periods (1988-2000 & 2001-2018).

Table 1.6:

Model Estimation for Spanish Banks, including NPLs, periods 1988-2000 & 2001-2018

Variable	Ayuso Model1	Model1 Replication GMM	Model1 Replication OLS	Model1 Replication GMM	Model1 Replication OLS
Period	1986-2000	2001-2018	2001-2018	1988-2000	1988-2000
Sample	142 banks	24 banks	24 banks	12 banks	12 banks
BUFi,t-1	0.40 (0.00)	0.51 (0.00)	0.77 (0.0)	0.24 (0.01)	0.69 (0.00)
ROEi,t	-0.43 (0.01)	0.06 (0.00)	0.05 (0.01)	-1.34 (0.00)	-0.14 (0.79)
NPLi,t	-1.99 (0.00)	0.54 (0.00)	0.55 (0.43)	-2.13 (0.00)	-1.35 (0.50)
BIGi,t	-14.06 (0.15)	-37.61 (0.67)	-3.52 (0.65)	-34.87 (0.24)	-5.78 (0.23)
SMAi,t	21.74 (0.12)	32.03 (0.00)	6.07 (0.59)	18.82 (0.05)	18.50 (0.04)
GDPGt	-4.09 (0.00)	-2.79 (0.00)	-3.64 (0.00)	-7.36 (0.00)	-5.81 (0.06)
m1	-4.65 (0.00)	-0.003 (0.99)	adjR ² =81.72%	0.16 (0.17)	adjR ² =78.41%
m2	0.16 (0.87)		DW= 1.40	-0.32 (0.74)	DW= 1.56
Sargan Test	114.15 (0.26)	20.92 (0.28)		4.40 (0.62)	

Notes: Model Estimation for Spanish Banks for the period 2001-2018 and comparison to the period 1988-2000 used by Ayuso et al. The dependent variable is BUF, p-values in brackets

As we can see from Table 1.6, the coefficient signs remain the same with the exception of ROE and NPL that switch to positive. Interestingly the NPL coefficient loses its significance when we estimate it with the Pooled OLS. The above is additional evidence that NPLs as a proxy for the banks risk appetite is not robust under all periods. To account for this drawback, we have introduced

the RWA density variable which better captures the risk profile of the institutions.

Our RWA density data are more complete from 2001 and onwards, therefore we have rerun the 2001-2018 period for the Spanish Banks replacing the NPLs with the RWA density.

Table 1.7

Model Estimation of Spanish Banks, including RWA_density, 2001-2018

Variable	Ayuso Model1	Model1 Replication GMM	Model1 Replication OLS
Sample	142 banks	24 banks	24 banks
BUF _{i,t-1}	0.40 (0.00)	0.58 (0.00)	0.89 (0.00)
ROE _{i,t}	-0.43 (0.01)	0.06 (0.00)	0.036 (0.05)
NPL _{i,t}	-1.99 (0.00)		
RWAdensity _{i,t}		0.50 (0.00)	0.22 (0.01)
BIG _{i,t}	-14.06 (0.15)	-13.94 (0.03)	-3.21 (0.69)
SMA _{i,t}	21.74 (0.12)	75.51 (0.00)	27.64 (0.03)
GDPG _t	-4.09 (0.00)	-2.45 (0.00)	-3.06 (0.01)
<hr/>			
m1	-4.65 (0.00)	-0.26 (0.79)	adjR ² =90.36%
m2	0.16 (0.87)	0.15 (0.74)	DW= 1.87
Sargan Test	114.15 (0.26)	17.35 (0.43)	

Notes: Model Estimation for Spanish Banks for the period 2001-2018 using RWA density as a proxy for failure costs and comparison to the period 1988-2000 used by Ayuso et al. The dependent variable is BUF, p-values in brackets

As we can see in table 1.7 above the inclusion of the RWA density variable is statistically significant in both our GMM and Pooled OLS model. In addition to this the adjR² of the Pooled OLS model has increased to 90.36%. Therefore, it seems that RWA density is superior in terms of capturing the risk profile of the institutions.

1.4.3 All European Banks during Period 1988-2018

We have now rerun our empirical results with our full dataset that includes all European Banks from 1988-2018. Table 1.8, shows how the results compare using both NPLs and RWA_density (Model1a & Model1b)

Table 1.8

Model estimation for period 1988-2018, including all European Banks

Variable	Ayuso Model1	Model1a	Model1b	Model2	Model3
Sample	142 banks	508 banks	508 banks	508 banks	508 banks
BUFi,t-1	0.40 (0.00)	0.05 (0.00)	-0.17 (0.00)	0.38 (0.00)	0.10 (0.01)
ROEi,t	-0.43 (0.01)	0.005 (0.20)	-0.0039 (0.00)	0.002 (0.38)	-0.003 (0.01)
NPLi,t	-1.99 (0.00)	5.17 (0.00)			
RWAdensity _{i,t}			2.73 (0.00)	1.14 (0.00)	1.63 (0.00)
BIGi,t	-14.06 (0.15)	-43.64 (0.37)	-204.19 (0.00)	-99.06 (0.25)	-40.93 (0.51)
SMAi,t	21.74 (0.12)	25.83 (0.01)	6.38 (0.73)	60.96 (0.08)	48.82 (0.14)
GDPGt	-4.09 (0.00)	-7.40 (0.00)	-2.20 (0.00)	-2.67 (0.05)	-1.14 (0.12)
BASELi,t		-3.25 (0.57)	-20.83 (0.00)	-3.84 (0.12)	-7.82 (0.00)
PROFITSi,t				0.012 (0.04)	0.004 (0.03)
LOANGi,t					0.007 (0.02)
m1	-4.65 (0.00)	-1.16 (0.24)	0.15 (0.87)	0.32 (0.74)	0.18 (0.85)
m2	0.16 (0.87)	0.98 (0.32)	-0.48 (0.62)	1.12 (0.25)	0.99 (0.32)
Sargan Test	114.15 (0.26)	115.53 (0.17)	144.06 (0.00)	59.25 (0.32)	66.23 (0.12)

Notes: Model Estimation for all European Banks for the period 2001-2018 using RWA density as a proxy for failure costs and comparison to the period 1988-2000 used by Ayuso et al. The dependent variable is BUF, BASEL: dummy variable reflecting the introduction of Basel III regulation; PROFITS: Profits; LOANG: Loan Growth

Unfortunately, after including the RWA density in our full dataset, Model1b fails to pass the Sargan Test which is evidence of endogeneity. Specifically, it seems that there is a missing/omitted variable that is correlated with both the independent variable and the error term and causes the model to fail the Sargan test. To address this issue, we performed multiple trials with different variables in the model and we identified that including Profits of each Institution rectifies the endogeneity issue. In Model2 we have included the Profits variable and we can see that we fail to reject the Sargan's H0 hypothesis, that instruments are not correlated with residuals.

1.4.4 Model Robustness

The next step is to examine the robustness of our new results by using an alternative extension of our initial model. In Model3 we have added the Loan Growth as an additional regressor similar to Ayuso et al Model3. The rationale behind the selection of Loan Growth is that we tried to add another procyclical variable that is proxying the interaction between credit supply and demand. Model3 shows the results after including Loan Growth and as we can see both the cyclical of the buffer remains unaffected with a strong negative relationship and the RWAdensity significance also remains unaffected. In Model 4-8, we have used a number of different specifications and explanatory variables. In all cases our results are robust with a positive and statistically significant RWAdensity and PROFITS variable and a significant cyclical of the buffer regardless if we use the actual realized GDP or the GDPFORECAST explanatory variable (source: IMF).

Table 1.9:

Estimation of Additional models to assess robustness

Variable	Model3	Model4	Model5	Model6	Model7	Model8
Sample	508 banks	508 banks	508 banks	508 banks	508 banks	508 banks
BUFi,t-1	0.10 (0.01)	0.35 (0.00)	0.38 (0.00)	0.11 (0.00)	0.16 (0.00)	0.22 (0.00)
ROEi,t	-0.003 (0.01)	-0.008 (0.01)	0.003 (0.31)	-0.004 (0.00)	0.002 (0.22)	0.001 (0.73)
RWAdensityi,t	1.63 (0.00)	2.70 (0.00)	1.14 (0.00)	1.62 (0.00)	1.83 (0.00)	1.52 (0.00)
BIGi,t	-40.93 (0.51)	-43.11 (0.36)	-103.95 (0.24)	-38.72 (0.50)	-66.86 (0.19)	-70.72 (0.29)
SMAi,t	48.82 (0.14)	76.26 (0.00)	58.44 (0.09)	49.10 (0.13)	9.86 (0.73)	51.98 (0.13)
GDPGt	-1.14 (0.12)	-1.33 (0.07)			-2.87 (0.05)	
BASELi,t	-7.82 (0.00)	-4.45 (0.09)	-3.32 (0.19)	-7.02 (0.00)	-9.65 (0.02)	-9.20 (0.00)
PROFITSi,t	0.004 (0.03)	0.003 (0.08)	0.013 (0.02)	0.005 (0.01)	0.005 (0.02)	0.016 (0.06)
LOANGi,t	0.007 (0.02)			0.006 (0.02)		
ROAi,t		0.70 (0.90)				
GDPFORECASTi,t			-3.05 (0.02)	-1.74 (0.07)		-1.11 (0.44)
BANK_CREDITi,t					-1.22 (0.00)	
COST/INCOME,t						-0.26 (0.04)
m1	0.18 (0.85)	0.21 (0.83)	0.23 (0.81)	0.24 (0.80)	0.63 (0.52)	-0.55 (0.57)
m2	0.99 (0.32)	1.12 (0.26)	1.13 (0.26)	1.00 (0.32)	1.06 (0.28)	1.18 (0.23)
Sargan Test	66.23 (0.12)	50.35 (0.13)	59.60 (0.31)	66.51 (0.12)	58.64 (0.31)	53.46 (0.18)

Notes: Model3 shows the results after including Loan Growth which is another procyclical variable that is proxying the interaction between credit supply and demand. Model 4-8 shows different specifications and explanatory variables to assess robustness. The dependent variable is BUF, ROA: Return on Assets; GDPFORECAST: IMF GDP growth forecast for next year; BANK_CREDIT: Bank Credit as percentage to GDP; COST/INCOME: cost income ratio; p-values in brackets

1.5 Policy Implications

According to the BCBS policy document on Global Systemic Banks, BCBS has adopted a series of reforms to enhance the resilience of banks and the overall banking system. The most important of these measures is the introduction of an additional pillar I requirement for the so called “global systemically important financial institutions (G-SIFIs)”. The additional buffer which ranges between 1%-3.5% is imposed to banks with the highest score coming from five categories. Each category is decomposed to indicators and each indicator is weighted accordingly as shown in the following Table (1.10).

Table 1.10

BCBS categories and Indicator weighting to assess GSIBs – Source: BCBS

Indicator-based measurement approach		
Category (and weighting)	Individual indicator	Indicator weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio	20%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

Notes: This table shows the BCBS indicators and weights used to calculate the GSIB capital buffer

As we can see in Table 1.10 the size of the Financial Institutions is the indicator which is weighted with a maximum weight of 20%. In addition, Complexity is another indicator which is weighted with a maximum weight of 20%. What we believe is missing, is the inclusion of an indicator that takes into account riskiness of the balance sheet as well. In this context our recommendation is that the policy makers should not only considers the Size (expressed as the total exposure absolute value) of the institution but also the percentage of the exposures that are deemed risky. We believe that the RWA density which was used earlier could be a very good additional indicator that can be included in the model and will penalize those institutions with higher risk exposures as a percentage of total Assets, instead of those institutions that may just have big Asset size regardless of how well hedged it may be. To ensure a level playing field for this comparison we further suggest that the calculation of the RWA density for the purpose of determining GSIBs is done using the standardized approach only which, according to Basel III, institutions will have to calculate in all circumstances for the whole Banking group as part of the mandatory BCBS output floor calculation. This is to ensure that banks that use advanced IMA models (both Market risk and Credit risk) do not have a benefit .

To prove this on Table 1.11 we have ranked the 30 largest banks in terms of Total Assets during the last ten years (period 2009-2018). As we can see the ranking based on the RWA density is materially different compared to the ranking based on the value of Total Asset Exposures that is used by BCBS. Let's take the example of Deutsche Bank. The German Bank is the 4th largest Bank in terms of Total Assets in Europe, however it is only ranked 29th in terms of RWA density which implies that the riskiness of its assets is lower compared to other Banks with lower absolute value of Assets. On the other side Standard Chartered is ranked 23rd in terms of Total Assets but is 4th when we look at the RWA density. More surprisingly Standard Chartered is on the 1st bucket (lowest risk) of the list of GSIB institutions (Table 1.12)

Table 1.11

Global ranking of Banks by Total Asset size (average of the period 2009-2018)

Largest Banks 2009-18	Assets in millions	Ranking based on Asset size	RWA density (10y average)	Ranking based on RWA densi
HSBC Holdings	2,523,725.20	1	41.94	7
BNP Paribas	2,476,132.45	2	30.80	15
Credit Agricole Group	2,224,490.58	3	29.18	19
Deutsche Bank	2,123,260.43	4	20.86	29
Barclays	1,974,974.45	5	27.94	22
Royal Bank of Scotland	1,683,577.51	6	31.68	14
Banco Santander	1,588,161.86	7	44.96	5
Societe Generale	1,540,530.93	8	27.82	23
Groupe BPCE	1,445,560.08	9	33.70	10
Lloyds Banking Group	1,322,534.60	10	32.39	13
HSBC Bank	1,199,813.05	11	27.49	24
ING Group	1,162,160.59	12	34.62	9
UBS	1,155,133.61	13	20.65	31
UniCredit	1,099,790.07	14	46.95	2
Credit Suisse Group	936,151.82	15	29.33	18
Credit Mutuel	862,426.12	16	32.91	11
HBOS	853,718.24	17	28.64	20
Intesa Sanpaolo	850,903.86	18	44.17	6
Rabobank Group	827,504.51	19	32.51	12
Banco Bilbao Vizcaya Argentaria	789,004.35	20	53.98	1
Nordea Group	769,582.91	21	25.64	26
Commerzbank	751,604.06	22	36.42	8
Standard Chartered	622,851.50	23	45.25	4
Danske Bank	563,682.58	24	24.56	27
Deutsche Zentral-Genossenschaftsbank	534,275.40	25	24.01	28
National Westminster Bank	519,622.66	26	29.42	17
ABN Amro Group	496,182.67	27	28.21	21
Santander UK	432,040.50	28	27.20	25
CaixaBank	414,058.09	29	45.27	3
Dexia	407,751.58	30	20.84	30

Notes: This table shows the 30 largest banks ranked according to Total Assets versus RWA density

Table 1.12:

List of GSIBs for 2018, Source Financial Stability Board

Bucket¹²	G-SIBs in alphabetical order within each bucket
5 (3.5%)	(Empty)
4 (2.5%)	JP Morgan Chase
3 (2.0%)	Citigroup Deutsche Bank HSBC
2 (1.5%)	Bank of America Bank of China Barclays BNP Paribas Goldman Sachs Industrial and Commercial Bank of China Limited Mitsubishi UFJ FG Wells Fargo
1 (1.0%)	Agricultural Bank of China Bank of New York Mellon China Construction Bank Credit Suisse Groupe BPCE Groupe Cr�dit Agricole ING Bank Mizuho FG Morgan Stanley Royal Bank of Canada Santander Soci�t� G�n�rale Standard Chartered State Street Sumitomo Mitsui FG UBS Unicredit Group

Notes: This table shows the GSIB capital buffer by systemic bank

Chapter II: The impact of Reversal Interest Rate on Bank's Profitability, Risk Taking, Leverage and Bank Activity

Abstract

Since the eruption of the recent Financial meltdown, monetary authorities have faced a challenging macroeconomic environment which among others involved economic stagnation, high unemployment and deflation for certain countries. To address this difficult situation monetary authorities lowered policy rates using conventional monetary practices. When policy rates reached the zero lower bound without achieving desired results on economic activity, most central banks introduced a number of unconventional monetary policies which among others included the introduction of negative interest rates policies (NIRP) to boost further economic stimulus. Using an initial dataset of 781 banks and a Difference-in-Difference (DiD) methodology this paper examines whether negative interest rate policy has achieved its goal. Our results indicate that NIRP was successful in de-risking banks' balance sheets but had a detrimental effect on lending and deposits. In addition, for capital adequacy and profitability we can see a detrimental effect using our basic methodology however the results are not robust under all methodology settings. Finally, we have also found evidence of the existence of a "Creeping-up effect" implying that low interest rates for long periods further amplify the effect of NIRP on lending.

2.1 Literature Review

According to Gauti et.al 2019, the need for nonconventional monetary policy is potentially strong due to the long-term drop-in interest rates to very low levels. There have been many countries have applied negative policy rates since 2014. In this article, the author reported the inability of financial intermediaries to pass negative central bank rates to deposit rates which remained close to zero. Using Sweden's banking statistics, a disconnect between the central bank rate and lending rates was identified, once the central bank rate went to the below zero territory. The author also showed that part of this disconnect is attributed to deposit funding. Interestingly the authors have showed that banks which rely on financing through deposits are less probable to decrease loan rates in response to rate cuts imposed by monetary authorities. In line with this, the author observed that after the deposit rate had become irresponsible, Swedish banks with large deposit shares experienced less credit expansion. Moreover, there has been evidence of negative excess returns of the Swedish bank stocks following the announcement of negative policy rates. The stock responses in the negative policy rate news was asymmetrical compared to announcements while on positive rates

As analysed by Bounou 2019 and in contrast with a positive rate environment, the effect of negative ratings on Interest margins of financial intermediaries is greater. The study finds that negative policy rates have compressed net interest margins of financial institutions and that lenders have compensated by elevating Non-interest costs (i.e commission and fees). In addition, the authors argue that negative policy rate declines have not led to additional risk-taking in order to compensate for the reduction in interest revenues. Finally, the effects of negative rates are also dependent on bank specific characteristics that can cause large variations between different banks. Finally, the study was unable to prove whether the reduction in risk-taking (measured by NPLs) during negative interest rates is attributed to (i) NPLs contracted before the implementation of negative rates with the effects

observable during the negative interest rate period or (ii) NPLs that have reduced due to the negative rates environment and a general equilibrium feedback mechanism from all unconventional monetary policies

The research of Lopez et al. 2019 noted that banks compensate for any unfavourable interest income related losses during a negative interest period, with reduced deposit expenditures and non-interest income gains. By increasing lending activity and rising their deposit share, banks adjust to negative rates. Due to the large heterogeneity among banks, the study is inconclusive on whether the monetary transmission mechanism remains unchanged during a negative interest rate environment. However, focusing only on small and high-deposit banks the study was able to prove that the conventional monetary transmission process works, since the transition into negative interest rates forces these types of financial institutions to withdraw asset holdings from very liquid instruments in order to expand lending. In general, the authors suggest limited effects for bank profitability of negative rates to date.

From the empirical findings of Boungou et al 2020, it is evident that in countries where negative rates were introduced, bank net interest margins (NIM) compressed. The Net Interest Margin squeezing originates from the hesitation of financial intermediaries to employ rates that are negative on retail deposit. Specifically, the study argues that loan rates offered by banks fall more rapidly compared to retail deposit rates in a negative interest rate setting. The authors also illustrated that the effect of NIRPs on Net Interest Margin is greater on smaller deposit-dependent banks. They also observed that retail deposit-dependent banks have increased their lending in reaction to NIRP. The introduction of NIRP had also a larger effect on smaller and less-capitalized banks.

Brunnermeier et al 2019, showed the theory behind the existence of a so called “reversal interest rate”, the interest rate below which central bank policy expansion has the opposite result and therefore becomes detrimental. The proposed theory depends on net interest income of financial institutions having

a larger decrease compared to capital gains coming from bank's holding of securities. Brunnermeier et al argued that the magnitude of the Reversal Interest Rate effect relies on the size of these capital gains and the initial equity capitalization of financial institutions. They also argued that the effect "creeps up over time", implying that a "low for long" interest rate environment is even more detrimental for lending and as a result the economy.

Bikker and Vervliet 2017, noted in their analysis that the environment of low interest rates actually impairs the profit effectiveness of banks and decreases net interest margins. However, institutions have decided to decrease provisioning in order to sustain their profit levels which in turn could jeopardize financial stability. The study argues that institutions did not increase trading operations and did not undertake greater risk exposures to compensate for profit losses as a response to low interest rates. That being said, over time, banks may change this decision and amend their operating models to be less focused on lending and financing activities. Finally, especially for credit loss provisions the author observed that in the reduced interest rate setting, banks decided to reduce their credit loss provisioning level which resulted in smaller buffers for potential unexpected shocks.

The study of Boungou 2021, noted that banks based in negative interest-rate countries have changed their bank-lending framework by promoting additional lending and reducing costs. The author indicates that banks have reduced lending costs and increased lending, particularly for loans beyond 3 months, in reaction to negative interest rates. By changing their lending behaviour, large and high-deposit banks have responded decisively to negative interest rates. In addition, it is observed that banks, in countries where NIRP has been applied, decided to reduce their overall risk taking in the years following the introduction of negative rates. This observation is mainly dependent on the specifics of the banking system of every country and in particular it is related to the size and level of capitalization of the banking system. In general, the author found that negative rates have a considerable influence on the conduct of bank lending.

The analysis of Molyneux et al 2019, noted that in countries adopting negative interest rate policies (NIRP), bank interest margins and overall profitability declined relative to non-adoptive countries. This negative impact also depends on the particular characteristics of these bank, such as their size, the composition of their balance sheet and capital structure, the business model and product specialty. The efficiency of the NIRP pass-through process could also be influenced by the stylized facts of the regional financial system, notably competition levels and also fixed/floating level of loans. In NIRP adopting countries, the bank's earnings and profitability have dropped more than in non-adopting countries. Specifically, NIRP affected countries had a 16.41% and 3.06% decrease in Net Interest Margins and ROA respectively, relative to the countries where the monetary authorities did not adopt negative rate policies. NIRP's effects on margins and profitability depends on various characteristics of the bank and region. Big banks are, for example, able to offset the adverse consequences of NIRP on Net Interest Margins and ROA when they hedge , diversify or shift interest-based market models to non-interest-based. This is not the case for smaller banks where negative rates seem to have greater influence on their profitability. In addition for those banking institutions that are not very big, have an 'interest income-oriented' approach, focus more on property/real estate and mortgage operations, borrow inside domestic borders, work on dynamic banking systems and have significant exposures on floating loan rates, the negative effect of NIRPs appears to have been much stronger on both margins and earnings.

The empirical work of Altavilla et al, 2017, showed that keeping rates low for long may have a detrimental effect on bank's profitability. Indeed, following a reduction in interest rates, NIM (i.e net interest margin) is not affected initially mainly due to a quicker repricing of the liability side versus the asset side. However, only after a long period of time, interest rate reductions do have a detrimental effect on profitability and this is explained by the fact that modifications in the rates applied on new business may take some time to reflect

in the outstanding loan balance. Therefore, a very prolonged low interest rate economy is detrimental for banks.

2.2 The Theory behind Reversal Interest Rate

Brunnermeier et al, 2019, where the first to introduce a theoretical partial equilibrium model that attempts to explain the existence of a Reversal interest Rate.

Their model assumes the existence of identical banks with the following balance sheet

Figure 2.1

Balance Sheet view of a representative Bank

A	L
Loans $L @ i^L$	Deposits $D @ i^D$
Safe Assets $S @ i$	Equity E_0

Notes: This figure shows the Balance Sheet view of a representative Bank with Loans and Safe Assets on the Asset side and Deposits and Equity on the Liabilities side

Safe Asset (S): Earns rate i which is chosen by the Central Bank. For example this can be a government bond

Loans (L): Demand for Loans that bank j faces indicated by $L(i_j^L)$,

i_j^L stands for the nominal rate on the loans that bank j issues, $L'(\cdot) < 0$, elasticity $\varepsilon^L(\cdot)$

Deposits (D): Each bank is related with depositors with intensive deposit supply $d(i^D)$, $d'(i^D) > 0$, elasticity $\varepsilon^D(\cdot)$.

There is also an activation spread η beyond which depositors search for better deposit rates such that if $i^D < i - \eta^D(i) \Rightarrow$ depositors start searching for other bank

Equity (E): Let $E_0(i_0)$ be the institution's equity preceding any policy rate move ($t=0$). (function of i)

$E_0(i)$ with $E'_0(i) < 0$: Banks' book equity captures capital gains (CG)/asset re-evaluation from unexpected change in I at $t=1$. Negative derivative indicates a maturity mismatch between Assets and Liabilities

The Timing of events is as follows: There are two periods, 0 and 1. i_0 indicates the policy rate between times 0 and 1 that was anticipated prior to the start of period 0. Central banks on the other hand set policy rate equal to i which may defer from the expected i_0

1. Central Bank unexpectedly changes i
2. Banks realize capital gains
3. Banks choose L, i^L, D, i^D, S to maximise their period 1 net worth
4. Next period profits realized

Financial Frictions

In this setup banks face two main financial frictions:

- a Capital Constraint has the form of $\psi^L L + \psi^S S \leq N_1$

Where ψ are risk-weights and attempts to capture existing Regulation (e.g. Basel III) and risk taking behaviour. Please note that given S is the safe assets it's risk weight is equal to zero making the constraint $\psi^L L \leq N_1$

and

- a Liquidity Constraint of the form of $\psi^D D \leq S$

which attempts to capture existing Reserve and Liquidity Requirements Regulation. The aim of the reserve requirement regulation and as a consequence of the constraint is to ensure that bank runs are avoided

Bank's problem

Bank will try to maximise its Net Worth at the period 1 by solving the below maximisation problem:

$$\begin{aligned} \max_{i^L, i^D, L, D, S, N_1} \quad & N_1 = (1 + i^L)L + (1 + i)S - (1 + i^D)D \\ & L + S = D + E_0(i) \\ & \psi^L L \leq N_1, \quad \psi^D D \leq S \end{aligned}$$

Where $L+S= D + E_0(i)$ is the balance sheet identity

Solving the above maximization problem by using a Lagrangian and taking the FOC yields the optimal rate on loans i^{L*}

$$i^{L*} = \underbrace{i}_{\text{Marginal opportunity cost}} + \underbrace{\frac{1}{\varepsilon^{L*}}}_{\text{Mark-up}} + \underbrace{\frac{\psi^L}{1 + \psi^L} \lambda^{L*}}_{\text{capital constraint}}$$

and the optimal rate on deposits i^{D*}

$$i^{D*} = \underbrace{i}_{\text{Marginal benefit}} - \underbrace{\frac{1}{\varepsilon^{D*}}}_{\text{Mark down}} + \underbrace{\frac{\psi^D}{1 + \psi^L} \lambda^{D*}}_{\text{Liquidity constraint}}$$

We can see that, on the basis that a financial institution can gain a return of i from keeping a fixed-income asset, i will represent the opportunity cost of issuing loans while institutions charge a mark-up on top of this. In similar context for deposits, institutions will use a mark down on the marginal investment rate i .

When constraints do bind the Lagrange multiplier are positive and indicate that institutions charge higher loan rates to reduce leverage. In similar context, institutions offer higher than anticipated deposit rates so as to increase their liquidity ratio.

ε^{L*} and ε^{D*} are semielasticities (elasticities in economics) calculated at the optimal point.

The above results implies that there is an Imperfect pass-through of changes in policy rates

- $i \rightarrow i^L > i$
- $i \rightarrow i^D \neq i$

Existence of Reversal Interest Rate

Reversal i^{RR} is defined as $\frac{dL^*}{di} \geq 0$ iff $i \leq i^{RR}$.

Implying that any further reduction on the policy Rate will decrease Lending. That is only possible if capital gains $E_0(i)$ are low (Brunnermeier's and Koby's first Proposition)

The intuition is as follows:

After applying the envelop theorem the bank's problem yields

$$\frac{dN}{di} = \mu E'_0(i) + (1 + \lambda^L)S$$

Where μ and λ^L are defined from the FOC of the initial Bank's problem.

Replacing them to the above equation yields:

$$\frac{dN}{di} = (1 + \lambda^L)[S + (1 + i)E'_0(i)]$$

and setting $E'_0(i) = CG$ (reflecting Capital Gains)

and

$$NII = \underbrace{i^{L*}L^* + iS^*}_{\text{interest income}} - \underbrace{i^{D*}D^*}_{\text{interest expenses}}$$

with $\frac{dNII}{di} = S$

yields the main result of the Bank's problem

$$\frac{dN_1^*}{di} = \underbrace{(1 + \lambda^{L*})}_{\text{Amplification}} \left(\underbrace{\left(\frac{dNII}{di}\right)}_{NII > 0} + \underbrace{(1 + i)\frac{dE_0(i)}{di}}_{CG < 0} \right)$$

The intuition is that there is a **Trade-off between two forces (Net Income and Capital Gains)**

- At the optimal point a reduction of the policy rate will reduce NII
- At the same time there is an offsetting effect from duration mismatch that generates some Capital Gains

Reversal Interest Rate effect occurs when

- NII force dominates (i.e maturity mismatch is very small generating small or zero Capital Gains)
- Net worth goes down causing the capital constrain to become binding and as a result Lending goes down
- An amplification effect happens when the institution's capital constraint becomes binding ($\lambda^{L*} > 0$.)

2.3 The Creeping-up effect

If the above two period model is expanded to more periods another result becomes more obvious. Specifically, Capital gains last only until bonds mature whereas Losses in NII after an interest rate reduction remain similar across all periods.

Conclusion is that a prolonged low-interest-rate economy will damage institutions Net interest profits in every time period while capital gains will also become lower but mainly in later periods

Figure 2.2:

The Creeping-up effect of low for long interest rates

	t=1	t=2	t=3	t=4
NII	$dNII/di$ (-)	$dNII/di$ (-)	$dNII/di$ (-)	$dNII/di$ (-)
CG	dE_0/di (+)	dE_0/di (+)	bonds matured	bonds matured

Notes: Prolonged low-interest-rates have a detrimental effect. Capital gains last only until bonds mature whereas Losses in NII remain similar across all low interest rate periods.

2.4 The dataset

We have created an incomplete structure of panel data and we have included 782 banks with data spanning from 2000 to 2018. We have separated the dataset into two groups: the “Control” group which includes banks that originate from countries that haven’t applied a NIRP and the “Treated” group which includes banks that are affected from the Negative Interest Rate Policy.

Our data include Balance Sheet Components (eg Total Loans, Total Assets), Capital Adequacy metrics (Capital Adequacy Ratio, Tier I capital, Tier II capital etc) and Riskiness Metrics (NPLs, Risk Weighted Assets). We used, among others, the FT Banker Database , Bloomberg, The Global Economy and IMF as

main sources to collect our data. We have further enriched our database with Macroeconomic data

Table 2.3:

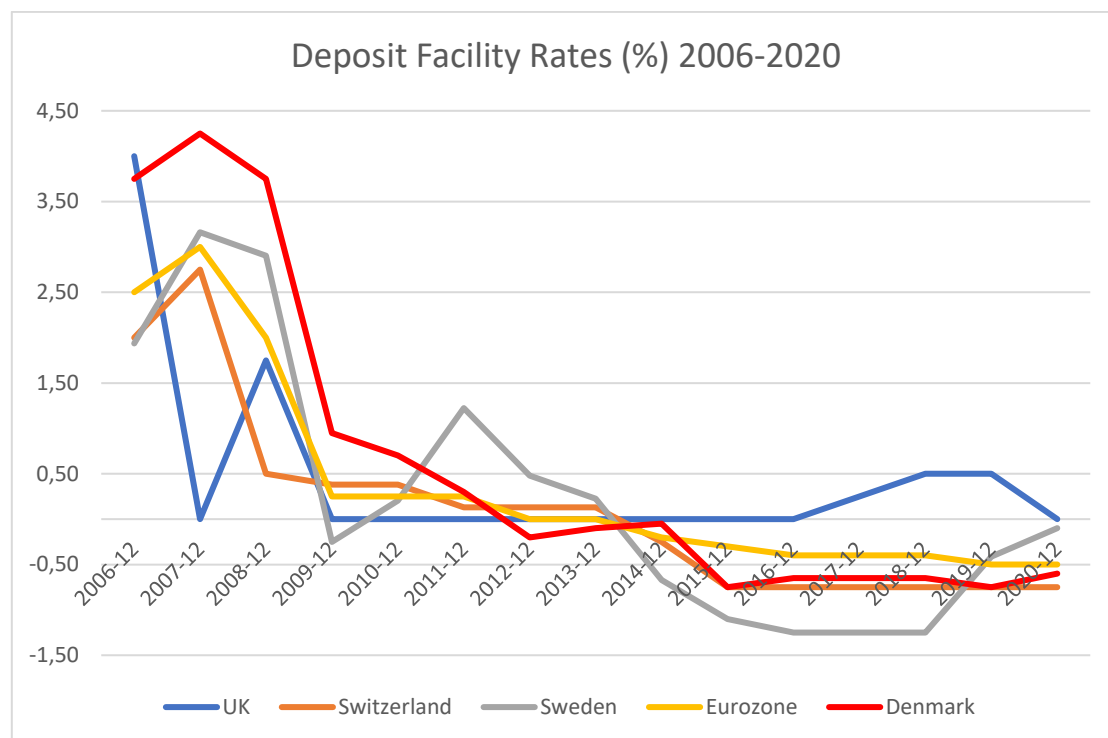
Number of Banks included in the Dataset and their respective Treatment

Country	Number of Banks	Group
Argentina	62	Control
Australia	33	Control
Canada	17	Control
Israel	8	Control
Poland	23	Control
Russia	127	Control
Serbia	24	Control
Turkey	38	Control
Iceland	5	Treated
Greece	7	Treated
Cyprus	8	Treated
Finland	8	Treated
Sweden	8	Treated
Belgium	11	Treated
Ireland	11	Treated
Malta	11	Treated
Portugal	14	Treated
Denmark	16	Treated
France	20	Treated
Luxembourg	20	Treated
Netherlands	20	Treated
Austria	26	Treated
Spain	26	Treated
Germany	50	Treated
Italy	50	Treated
Switzerland	66	Treated
UK	73	Treated
Total	782	

Notes: 782 banks with data spanning from 2000 to 2018. Control” group includes banks that originate from countries that haven’t applied a NIRP whereas “Treated” group includes banks that are affected from the Negative Interest Rate Policy

Figure 2.4:

Deposit Facility Rates from 2006-2020 for selection of Central Banks of our sample



Notes: 2014 is the year where all countries of our Treated Group have turned to negative interest rates with the period (P) before this the pre experiment period (P=0) and the period from 2014 and onwards the post experiment (P=1) period

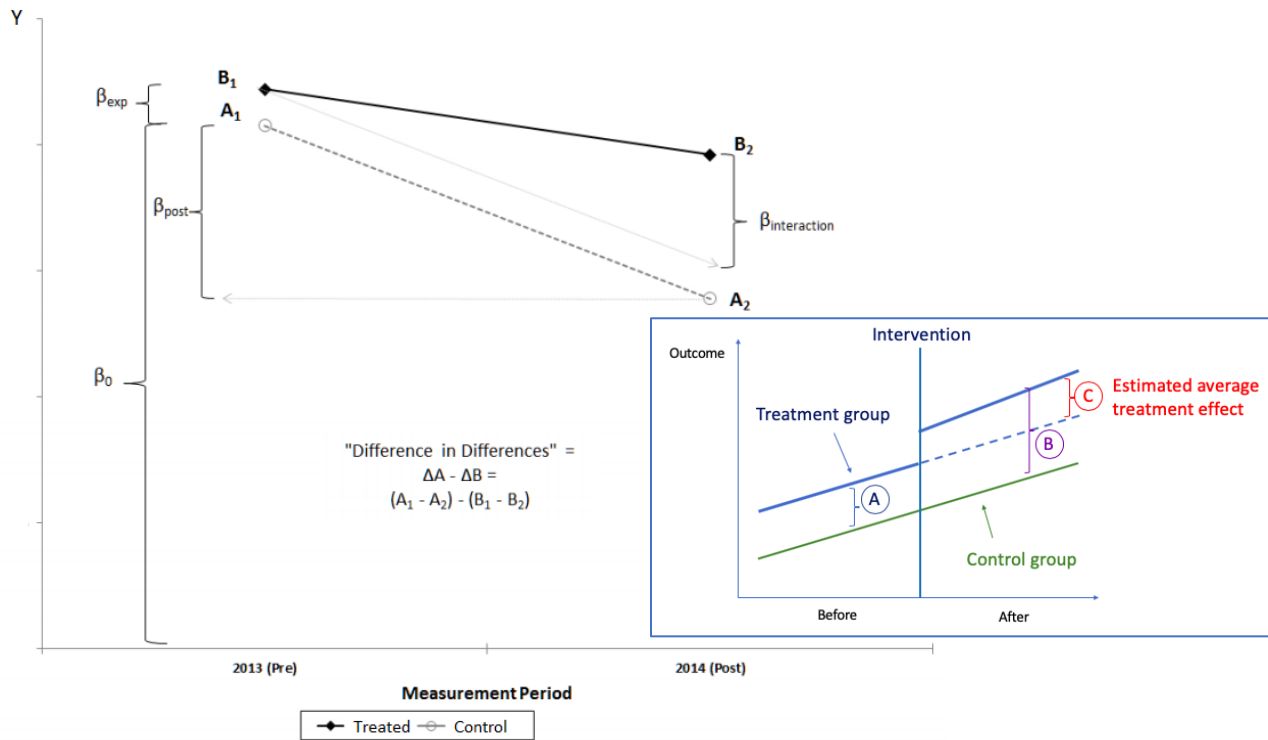
2.5 Empirical Model

Our next step is to adopt a DiD empirical strategy. The DiD specification is used widely in experimental researches when researchers try to model the effect of a particular treatment in the Treated group of an experiment. This approach has also been extensively applied in policy evaluation literature and lately to the economic science (Beck, 2010, Calderon et al, 2013, Berger, 2014).

The empirical specifications requires two groups, one that has received the treatment and one that remains untreated (control group). In our case the Treatment group are those banks where their countries' monetary authorities have applied a Negative interest Rate Policy (NIRP) and the control group those banks where their countries' monetary authorities have not applied a Negative interest Rate Policy (NIRP). By including a control group in a DiD model, any bias caused by omitted variables common across the treated and control groups is implicitly controlled, even when these variables are unobservable. For example, regulatory reforms (like Basel3 or CRR3) expected to impact treated and untreated bank indicators similarly, in spite of the NIRP introduction. Given that these changes are expected to impact institutions in a similar way, the DiD methodology overcomes the bias by differencing away similar trends that simultaneously impact treatment and control group.

The DiD specification requires also the definition of the pre and post experiment period. During first period, neither treated or control is undergoing the treatment. During the second period, just one group undergoes the treatment. In our case we define 2014 as the year where all countries of our Treated Group have turned to negative interest rates with the period before this the pre experiment period and the period from 2014 and onwards the post experiment period.

Difference-in-Differences with Model Coefficients



Our model then becomes:

$$Y_{i,j,t} = a + \beta_1 Period_t + \beta_2 Treated_j + \beta_3 (Period_t * Treated_j) + \gamma_1 Country_Controls_i + \gamma_2 Bank_Controls_i + \varepsilon_{i,j,t}$$

Our coefficient of interest is β_3 which is capturing the effect of the interaction i.e the diff in slopes between Treated and Control group.

Ignoring the Bank and Country Specific Controls and taking into account the above equation, we could demonstrate that the interaction coefficient provides the estimate and inference of the DiD.

$$\Delta A - \Delta B =$$

$$(\alpha - [\alpha + \beta_1]) - ([\alpha + \beta_2] - [\alpha + \beta_1 + \beta_2 + \beta_3]) =$$

$$(\alpha - \alpha - \beta_1) - (\alpha + \beta_2 - \alpha - \beta_1 - \beta_2 - \beta_3) =$$

$$(-\beta_1) - (-\beta_1 - \beta_3) = \beta_3$$

2.6 Empirical Results

We have reviewed the effect of Negative Policy Rates on four type of variables a) Bank Risk Appetite/Riskiness variables b) Bank Operations c) Bank Profitability and d) Capital and Liquidity

2.6.1 Propensity Score Matching

Furthermore, in order to ensure robustness, we have applied propensity score matching techniques which we combine with the DiD methodology. That way by pairing treated and control banks, allows us to select banks that have similar characteristics.

Specifically, one of the DiD prerequisites is that the control group forms a close counterfactual for the treatment. We examined the assumption by creating a control sample via propensity score matching (PSM) similar to what has been proposed by Rosenbaum et al in 1983. The PSM probability of every bank is calculated using a Logit regression. We used two sets of bank specific and macroeconomic variables to match banks under NIRP treated and non-treated countries during the pre-treated period (i.e prior to 2014).

Table 2.5:

Macroeconomic and bank Specific variables included in the Propensity Score Model

Variable	Type	Observations
Cost/Income Ratio %	Bank Specific	6775
RWA Density %	Bank Specific	6775
BIS Total %	Bank Specific	6775
Total Deposits / Assets	Bank Specific	6775
Impairments / Total Loans	Bank Specific	6775

log(Assets)	Bank Specific	6775
Economic growth	Macaoeconomic	6775
Inflation as a percentage change of CPI	Macaoeconomic	6775
Non-performing loans as percentage of all bank loans of the Country	Macaoeconomic	6775

Notes: Macroeconomic and Bank specific variables used to construct the PSM model. The PSM probability of every bank is then calculated using a Logit regression

The PSM Logit model is shown below:

$$p_i = Pr(D_i = 1 | X_{ijt}) = \frac{1}{1 + e^{-(x'_{ijt}\beta)}}$$

where D_i acts as a dummy describing the status of treatment, taking the value $D = 1$, when the institution has been impacted by Negative interest Rates, and zero in all other cases.

X_{ijt} is a matrix of observable macroeconomics factors, institution specifics and some Country Fixed effects in the pre-NIRP period (i.e prior to 2014)

The propensity score can be interpreted as the probability of a certain bank getting the Negative interest Rate treatment. In this case we have estimated the below PSM model with the following results

Table 2.6:

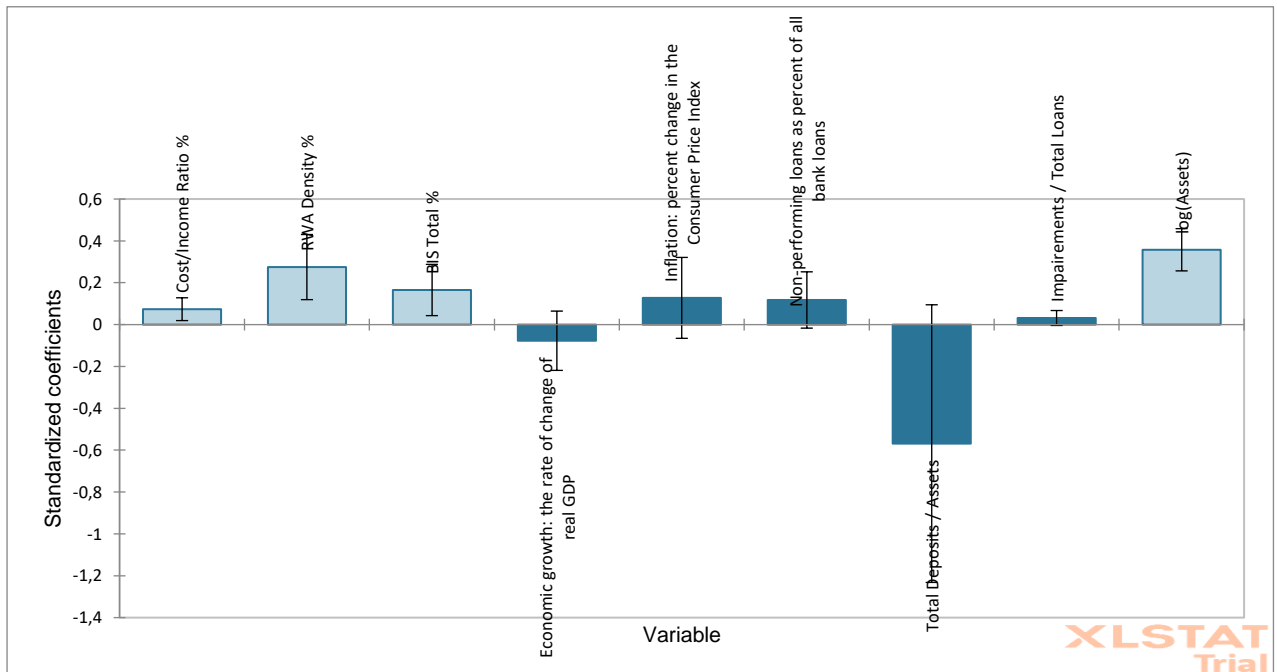
Output of the PSM Logit regression

Source	Value	Standard error	Wald Chi-Square	Pr > Chi ²	Wald Lower	Wald Upper
Cost/Income Ratio %	0,074	0,028	7,029	0,008	0,019	0,128
RWA Density %	0,275	0,079	11,997	0,001	0,119	0,430
BIS Total %	0,165	0,062	7,014	0,008	0,043	0,288
Economic growth: the rate of change of real GDP	-0,077	0,072	1,133	0,287	-0,219	0,065
Inflation: percent change in the Consumer Price Index	0,128	0,099	1,677	0,195	-0,066	0,321
Non-performing loans as percent of all bank loans	0,118	0,069	2,944	0,086	-0,017	0,252
Total Deposits / Assets	-0,569	0,338	2,822	0,093	-1,232	0,095
Impairments / Total Loans	0,032	0,018	3,018	0,082	-0,004	0,067
log(Assets)	0,358	0,052	48,170	<0,0001	0,257	0,458
Country Fixed Effects	YES					

Notes: Banks with increased Cost/Income Ratio, with riskier balance sheet (high RWA density), higher Impairments and larger size increase the odds of being impacted by negative rates.

Figure 2.7:

PSM model Standardized coefficients



Notes: PSM model Standardized coefficients with 95% conf. interval

We can observe that banks with increased Cost/Income Ratio, with riskier balance sheet (high RWA density), higher Impairments and larger size increase the odds of being impacted by negative rates. Also banks in countries that face higher inflation also increase the odds of being affected by a NIRP. On the other hand, institutions operating in countries with higher Economic growth and high Deposits decrease the odds of being affected by a NIRP

Following the estimation of the model we have estimated the individual propensity scores of each bank for each year and we have applied a canned “Greedy” Matching algorithm process (i.e using XLSTAT statistical software) with a caliper radius of $0.2 * \text{sigmas}$ (standard deviations of the propensity score logit)

We can observe in table 2.8 that 22% of participant Banks under the Treatment group were not matched to any candidates within the Control group. This implies that no participants were identified within the radius of $0.20 * \text{sigma}$.

Table 2.8:

Number of observations where a matching was possible

Categories	Number	Matched	Percentages	Unmatched	Percentages
Treated Observations	3816	2959	78%	857	22%
Control Observations	2959	2959	100%	0	0%

Notes: Table shows that 22% of participant Banks under the Treatment group were not matched to any candidates within the Control group. This implies that no participants were identified within the radius of $0.20 * \text{sigma}$.

Table 2.9:

Sample of the Propensity Score Matching results

Treatment	Logit(Propensity score)	Control	Logit(Propensity score)	Distances
Treated1	0,653	Control1901	0,651	0,002
Treated2	0,653	Control1752	0,655	0,002
Treated3	0,753	Control217	0,752	0,001
Treated4	0,600	Control3360	0,598	0,002
Treated5	0,612	Control1148	0,612	0,000
Treated6	0,650	Control907	0,651	0,001
Treated7	1,177	Control1571	1,180	0,004
Treated8	1,036	Control2509	1,035	0,000
Treated9	0,982	Control3558	0,986	0,004
Treated10	1,051	Control966	1,053	0,003
Treated11	1,052	Control2763	1,063	0,012
Treated12	1,157	Control2514	1,157	0,000
Treated13	1,207	Control1578	1,201	0,006
Treated14	1,246	Control270	1,232	0,016
Treated15	1,265	Control1577	1,267	0,002
Treated16	1,243	Control2768	1,268	0,028
Treated17	1,254	Control3629	1,277	0,026
Treated18	1,169	Control2510	1,158	0,013
Treated19	1,167	Control3560	1,154	0,014
Treated20	1,314	Control3627	1,308	0,007
Treated21	1,389	Control1636	1,382	0,008
Treated22	1,208	Control3367	1,200	0,009
Treated23	1,228	Control1572	1,216	0,014
Treated24	1,231	Control1575	1,194	0,042

Notes: Table shows the first 24 observations of the Treatment group matched with the Control Group

2.6.2 Bank Operations

The results from estimating our empirical equations can be found in the below tables. Our variable of focus is *Period * Treated* and its corresponding coefficient β_3 . This coefficient is the DiD estimator which is shown in the below tables as NIRP and reflects the on average difference in the change of the dependent variable between institutions within countries that are impacted by NIRP and institutions within countries where NIRP has not been applied

In this section we have reviewed the impact of Negative Rates on the activity and operations of banks. In Table 2.10 below we have assessed the impact of

NIRP on Total Deposits, Total Loans, Size and the Bank's Balances held at the Central Banks in our group of focus versus the banks in our control group (using the full dataset). Table 2.11 assesses the same variables but using only the Propensity Score Matched banks.

As we can see from the results of table 2.10 there is a negative and statistically important relationship at 1% confidence between NIRP and Total Loans Specifically, Total Loans have reduced on average by 19.15% compared to the control group. This result implies that banks have chosen to reduce the number of loans provided which is also in line with our following empirical finding related to the reduction of Credit RWAs (by 22.72% in Table 2.12). This is a very important result as it also demonstrates the existence of the Interest Rate Reversal effect. The result remains consistent even when we use the banks indicated by the PSM exercise. As we can see in table 2.11 the negative and statistically significant coefficient remains and is equal to 19.11%

Looking at Deposits held by Banks we can see in table 2.10 that Total Deposits reduced by 12.93% compared to the Control Group which is expected given that Banks from their nature tend to pass the lower policy rates to their customers. As a result lower deposit rates which in some cases are close to zero will force depositors to look on alternatives investments to achieve better returns (eg mutual funds, bonds etc) as they are not willing to suffer the additional mark down imposed by banks as expressed in the Rate Reversal Theory. This result remains consistent when we look at the PSM regressions in table 2.11 where the effect on deposits is statistically significant showing a reduction equal to -14.45% compared to the Control Group.

Regarding, balances kept at the Central Banks by individual Banks. The expectation here would be that the introduction of Negative Rates would force banks to retain a minimum level of deposits at the Central Bank, so that they are not charged with Negative Rates. Our results are aligned with this expectation, with a reduction of 1.87% compared to the control group which is statistically significant at 10% (p-value of 0.08%). The small reduction can be justified from

the fact that Central banks charge the negative Rates only on the excess amount of the required reserves and not on the mandatory part. The reduction is larger when we look at the PSM matched banks on table 2.11 equal to -3.07% with a 0.00% p-value.

Finally, in this section we have reviewed the impact of a NIRP to the overall Asset Size of the banks. According to the theory proposed by Brunnermeier and Kobby when the capital constraint binds, then at that point the policy rate reaches the “reversal interest rate”, as any additional decrease in i is going to reduce profits, which via the constraint will reduce L (Loans). As a result, banks will issue less Loans resulting to a reduction on the overall Asset Size of the banks. Our empirical result support this theory especially when looking at the empirical results of table 2.11 with the PSM matched banks. The results in table 2.11 indicate a statistically significant 8.82% reduction of the Asset Size of the banks versus the control group for the PSM matched banks.

Table 2.10:

Effect of NIRP on the activity and operations of banks (Full Sample)

BANK OPERATIONS								
	Deposits / Total Assets		Total Loans /Total Assets		Balances at the Central Bank / Total Assets		Bank Size	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,723631	0,00	0,579355	0,00	0,12106	0,00	3,93918	0,00
Period	0,173044	0,00	0,198994	0,00	0,04724	0,00	-0,06140	0,09
Treated	0,094749	0,00	0,148262	0,01	0,00959	0,38	0,37684	0,00
NIRP	-0,129353	0,00	-0,191532	0,00	-0,01876	0,08	0,04179	0,37
GDP Growth	-0,017143	0,00	-0,013725	0,00	-0,00221	0,00	-0,01575	0,00
Inflation	-0,011766	0,00	-0,00962	0,00	-0,00128	0,00	-0,04229	0,00
Size	-0,037849	0,00	-0,008225	0,27	-0,01818	0,00		
R-squared	0,192112		0,213837		0,10465		0,16216	

Notes: Table shows a negative and statistically important relationship at 1% confidence between NIRP and Total Loans Specifically, Total Loans have reduced on average by 19.15% compared to the control group.

Table 2.11:

Effect of NIRP on the activity and operations of banks (Propensity Score Matched Banks)

BANK OPERATIONS (Propensity Score Matched Banks)								
	Deposits / Total Assets		Total Loans /Total Assets		Balances at the Central Bank / Total Assets		Bank Size	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,537877	0,00	0,414091	0,00	0,14092	0,00	3,59889	0,00
Period	0,182568	0,00	0,195414	0,00	0,05791	0,00	0,05959	0,09
Treated	0,127237	0,00	0,199675	0,00	0,00480	0,15	0,64786	0,00
NIRP	-0,144536	0,00	-0,191163	0,00	-0,03072	0,00	-0,08827	0,07
GDP Growth	-0,009077	0,00	-0,006485	0,00	-0,00154	0,00	-0,00030	0,93
Inflation	-0,00891	0,00	-0,006005	0,00	-0,00203	0,00	-0,02787	0,00
Size	-0,006703	0,04	0,014262	0,00	-0,02160	0,00		
R-squared	0,180822		0,193764		0,13708		0,15808	

Notes: Table shows the negative and statistically significant coefficient remains when looking at the PSM banks and is equal to 19.11%. We can also see that Total Deposits reduced compared to the Control Group which is expected given that Banks from their nature tend to pass the lower policy rates to their customers

2.6.3 Risk Appetite & Riskiness

In order to assess the impact of NIRP on Bank's Riskiness and Appetite we have used the Credit RWAs, Market RWAs and NPLs as dependent variables that better reflect the amount of risk banks carry on their balance sheets. For the RWAs specifically we have transformed them to densities by dividing with Total Assets. We have also included GDP Growth and Inflation as country specific controls and Bank size (i.e the logarithm of Total Assets) as bank specific controls.

As we can see from the results of table 2.12 (full sample) there is a negative and statistically important relationship at 1% confidence of the NIRP and Credit RWA over Total Assets ratio, indicating that the average Credit RWAs have been reduced following the introduction of a Negative Rates as compared to the

countries that have not adopted the policy (Control Group). Specifically, Credit RWAs decreased on average by 22.73% compared to the Control group, which implies that there has been a de-risking of the banks' balance sheets following the introduction of NIRP. From the nature of Credit RWAs a reduction is possible either from reducing the number of Total Loans or from investing on safer Assets. The result is expected given that the Rate Reversal Theory expects a reduction in Lending activity and as a consequence Credit RWAs will reduce. The significant reduction of Credit RWAs is an additional indication of Rate Risk Reversal. The reduction is even higher when we look at the results of the PSM matched banks in table 2.13 equal to a statistically significant -24.84%

Looking at the Market Risk RWAs and how they relate with NIRP, we can see a negative and statistically significant relationship at the 1% level. Specifically, Market RWAs have reduced on average by 1.15% compared to the control group. This result implies that banks have chosen to take less market risk which is possible from investing in less volatile assets (i.e Safe assets). Market Risk RWAs from their nature include the ten-day Value at Risk which is a function of assets volatility. The reduction is even higher when we look at the results of the PSM matched banks in table 2.13 equal to a statistically significant -1.56%

The last variable that has been reviewed is the level of Non Performing Loans (%). Looking at the full sample this variable is insignificant in Table 2.12 with a coefficient of 0.82% and p-value of 13% as compared to the Control group. However, the variable becomes significant when we look at the PSM matched banks. The positive sign indicates that the introduction of a NIRP in our group of focus didn't have the desired effect of reducing the NPL as compared to the control Group

Table 2.12:

Effect of NIRP on the Risk Appetite and Riskiness of banks (Full Sample)

RISK APETTITE & RISKINESS						
	Credit RWA / Total Assets		Market RWA / Total Assets		NPL (%)	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,11452	0,00	0,011794	0,00	8,09990	0,00
Period	0,200442	0,00	0,010686	0,00	0,84862	0,01
Treated	0,294116	0,00	0,015909	0,00	-0,87109	0,01
NIRP	-0,227289	0,00	-0,01158	0,00	0,82532	0,13
GDP Growth	0,00275	0,49	0,000101	0,80	-0,34584	0,00
Inflation	-0,003952	0,01	-0,000139	0,01	0,03842	0,36
Size	0,004727	0,26	-0,001158	0,13	-0,70054	0,00
R-squared	0,25289		0,018559		0,04825	

Notes: Table shows a negative and statistically important relationship at 1% confidence of the NIRP and Credit RWA over Total Assets ratio, indicating that the average Credit RWAs have been reduced following the introduction of a Negative Rates as compared to the countries that have not adopted the policy

Table 2.13:

Effect of NIRP on the Risk Appetite and Riskiness of banks (Propensity Score Matched Banks)

RISK APETTITE & RISKINESS (Propensity Score Matched Banks)						
	Credit RWA / Total Assets		Market RWA / Total Assets		NPL (%)	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,028255	0,04	0,007708	0,01	1,64399	0,00
Period	0,230751	0,00	0,014612	0,00	1,42134	0,00
Treated	0,306147	0,00	0,016689	0,00	-0,60805	0,00
NIRP	-0,248453	0,00	-0,015637	0,00	1,21823	0,00
GDP Growth	0,002539	0,01	0,000147	0,45	-0,10984	0,00
Inflation	-0,002034	0,00	-5,04E-05	0,60	-0,00098	0,91
Size	0,020233	0,00	-0,000582	0,41	0,20007	0,00
R-squared	0,266329		0,021759		0,04499	

Notes: The reduction is even higher when we look at the results of the PSM matched banks. The significant reduction of Credit RWAs is an additional indication of Rate Risk Reversal.

2.6.4 Capital Adequacy

We have further looked at the effect of NIRP on Capital Adequacy. In tables 2.14 and 2.15 below we have reviewed the NIRP effect on the Total BIS Capital Adequacy Ratio, Tier 1 Capital and Total Equity Capital.

Looking at the leverage ratio, we can observe in both the Full sample (Table 2.14) and the PSM matched banks (Table 2.15) a statistically significant reduction in leverage of 3.9%. According to Brunnermeier when the capital constraint becomes binding, institutions offer higher-than-desired loan rates in order to reduce Lending and as a result their overall leverage.

More importantly we have checked the consequence of a NIRP on equity capital. We have examined both CET1 (Core Equity Tier1) and Total Tier 1 Capital. According to the Theory when Net Interest Income dominates then Net Worth goes down and as a result Capital reduces.

Surprisingly we can see that in both the full sample and the PSM matched banks Total Tier 1 Capital /Total Assets is statistically significant but shows an increase on average by 1% when compared to the Control Group of the full sample. The result remains consistent even after comparing against the PSM matched banks in Table 2.15

We believe that this result is explained from the fact that Total Tier 1 Capital also includes additional Capital components called AT1 (Additional Tier1) that distort the relationship. Therefore, we have examined Core Equity Tier1 that includes only Common Share, Retained Earnings and Stock Surplus. The results for Core Equity Tier1 are as expected with a statistically significant reduction of 7% for the PSM matched banks (compared to -1.18% for the full sample).

Table 2.14:

Effect of NIRP on the Capital Adequacy of banks (Full Sample)

CAPITAL ADEQUACY						
	Leverage Ratio		Total Tier1 Capital / Total Assets		Core Tier1 Capital / Total Assets	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	-0,05034	0,00	0,261556	0,00	0,264562	0,00
Period	0,003437	0,89	0,006393	0,35	0,015929	0,00
Treated	0,022852	0,00	0,001016	0,78	0,019705	0,00
NIRP	-0,038976	0,05	0,004156	0,48	-0,01855	0,00
GDP Growth	-0,001439	0,21	0,000928	0,07	0,001429	0,00
Inflation	0,000797	0,32	0,000921	0,00	0,005554	0,00
Size	0,051792	0,00	-0,044412	0,00	-0,046871	0,00
R-squared	0,039155		0,261285		0,269147	

Notes: Table shows a statistically significant reduction in leverage and Core Equity Tier1 which is additional evidence of the Interest Rates Reversal effect.

Table 2.15:

Effect of NIRP on the Capital Adequacy of banks (Propensity Score Matched Banks)

CAPITAL ADEQUACY (Propensity Score Matched Banks)						
	Leverage Ratio %		Total Tier1 Capital / Total Assets		Core Tier1 Capital / Total Assets	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	-4,4132	0,00	0,297338	0,00	0,210131	0,00
Period	0,3097	0,79	0,00222	0,51	0,083416	0,00
Treated	3,3866	0,00	-0,006047	0,02	-0,002294	0,68
NIRP	-3,8889	0,01	0,009077	0,05	-0,070406	0,00
GDP Growth	-0,2053	0,06	0,000543	0,09	-0,000187	0,79
Inflation	0,0579	0,31	0,000409	0,02	0,003833	0,00
Size	4,9729	0,00	-0,05077	0,00	-0,030195	0,00
R-squared	0,03465		0,267388		0,151726	

Notes: Reduction in leverage and Core Equity Tier1 remains consistent even after comparing against the PSM matched banks

2.6.5 Profitability

In this last section, we have reviewed the impact of Negative Rates on the Profitability of banks. In this context we have evaluated the impact of NIRP on Net Interest Income, Net Interest Expenses and Cost-to-Income Ratio.

The DiD coefficient against Net Interest Income / Assets, a proxy for Net Interest margin, is statistically significant and negative in both tables 2.16 (full sample) and 2.17 (PSM matched Banks). This result further strengthens the hypothesis of existence of Interest Rate Reversal effect. According to theory of Brunnermeier et al when the Capital gains are sufficiently low and NII force is negative then it dominates. The sign is in accordance to the findings of both Molyneaux et al. (2019) and Boungou et al. (2020) but in both these studies they evaluated the NIRP effect on the actual net interest margins of the banks.

In our setup, net interest Income is denoted as Interest Income minus Interest Expenses which is in essence the income generated by interest-bearing assets minus the interest burden of liabilities. We would expect interest expenses to have a negative relationship with the NIRP as long as banks can pass through reduced interest rates to depositors. The DiD coefficient against interest Expenses is indeed inline with this expectation, statistically significant and imply that Interest Expenses have reduced on average by -1.91% compared to the control group of the full sample and -2.09% of the PSM matched banks. The finding is inline to the findings of Boungou et al (2020) who reviewed the effect of NIRP on the interest paid on customers deposits.

Finally, we reviewed the Net non-Interest Income. This essentially Includes bank fees and is not statistically significant (p-value = 45%) in both the full sample (Table 2.16) and the PSM matched banks (Table 2.17).

Table 2.16:

Effect of NIRP on the Capital Adequacy of banks (Full Sample)

PROFITABILITY (excl outliers)						
	Net Interest Income/Total Assets		Net non-Interest Income / Total Assets		Net Interest Expenses/Total Assets	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0.030851	0.0000	0.036782	0.0000	-0,002613	0,22
Period	0.002259	0.0000	7.71E-05	0.9571	0,023647	0,00
Treated	-0.004692	0.0000	-0.001027	0.4025	0,005018	0,00
NIRP	-0.003482	0.0000	0.001244	0.4481	-0,019126	0,00
GDP Growth	-0.000110	0.3298	-0.000292	0.0534	-0,000382	0,16
Inflation	8.21E-05	0.5022	0.000956	0.0009	0,000246	0,13
Size	-0.002556	0.0000	-0.005651	0.0000	0,000552	0,08
R-squared	0.138275		0.088580		0,339193	

Notes: The coefficient against Net Interest Income / Assets, a proxy for Net Interest margin, is statistically significant and negative. This result further strengthens the hypothesis of existence of Interest Rate Reversal effect

Table 2.17

Effect of NIRP on the Capital Adequacy of banks (Propensity Score Matched Banks)

PROFITABILITY (Propensity Score Matched Banks)						
	Net Interest Income/Total Assets		Net non-Interest Income / Total Assets		Net Interest Expenses/Total Assets	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,032847	0,00	0,068039	0,0	0,001043	0,06
Period	0,002766	0,00	0,003786	0,0	0,027844	0,00
Treated	-0,005448	0,00	-0,015046	0,0	0,000254	0,46
NIRP	-0,004038	0,00	-0,00367	0,1	-0,020916	0,00
GDP Growth	-2,38E-05	0,66	-0,001168	0,0	-0,000249	0,00
Inflation	0,000213	0,00	-0,001411	0,0	0,000112	0,00
Size	-0,002877	0,00	-0,008591	0,0	-0,00027	0,04
R-squared	0,196823		0,124444		0,385422	

Notes: Reduction Net Interest Income remains consistent even after comparing against the PSM matched banks

2.6.6 Effect of Rate Changes during NIRP periods

At this point we have used a similar DiD setup and examined how policy Rate Changes affect the three main variables that contribute in the Rate reversal as presented in the Brunnermeier et al theory. The following empirical models were estimated

$$Y_{i,j,t} = a(\Delta Rates_i) + \beta_1 Period_t * \Delta Rates_i + \beta_2 Treated_j * \Delta Rates_i + \beta_3 (Period_t * Treated_j * \Delta Rates_i) + \gamma_1 Country_Controls_i + \gamma_2 Bank_Controls_i + \varepsilon_{i,j,t}$$

The coefficient of interest is β_3 that is related to the triple interaction term. It shows how a change in Policy Rates affect Loan Changes, Changes in Tier1 Capital and Changes in Net Interest Income during and NIRP period against a similar change in the control group

Table 2.18

Effect of NIRP Rate Changes on beta

Change in Tier1 Capital , Loans , NII (Propensity Score Matched Banks)									
	Change in Tier1 Capital			Change in Total Loans			Change in Net Interest Income		
	Coefficient	Std Error	PValue	Coefficient	Std Error	PValue	Coefficient	Std Error	PValue
a(Δ rates)	0.000222	0.000199	0.2637	-0.005109	0.004270	0.2316	0.000235	0.000282	0.4055
β_1 (Period * Δ rates)	-0.012559	0.002770	0.0000	-0.004330	0.004623	0.3490	-0.023164	0.003600	0.0000
β_2 (Treated* Δ rates)	-0.018818	0.014529	0.1953	-0.008918	0.012887	0.4890	-0.015063	0.018242	0.4090
β_3 (Period * Treated* Δ rates)	0.194372	0.054404	0.0004	0.375965	0.054568	0.0000	0.179263	0.068661	0.0091
GDP Growth	0.015766	0.002429	0.0000	0.021509	0.001881	0.0000	0.025488	0.003132	0.0000
Inflation	0.013961	0.001582	0.0000	0.003588	0.001505	0.0172	0.018861	0.002047	0.0000
Size	0.017104	0.002567	0.0000	0.009393	0.002023	0.0000	0.000135	0.003256	0.9670
R-squared	0.017971			0.034541			0.022865		

Notes: Table shows that coefficient of the interaction terms is positive which implies that during a NIRP period a negative move of 1% in the policy Rates will on average have 19.43% negative effect on Tier1 Capital compared to the Control Group

As we can see the coefficients for all interaction terms of Table 2.18 are positive which implies that during a NIRP period a negative move of 1% in the policy Rates will on average have 19.43% negative effect on Tier1 Capital compared to the Control Group. Similarly for Gross Total Loans the average effect is 37.5% versus the control Group and for Net Interest Income the negative effect is 6.86% versus the Control Group

This results are in alignment with the hypothesis of existence of Interest Rate Reversal effect. According to theory of Brunnermeier et al when the Capital gains are sufficiently low and NII force is negative then it dominates causing Capital to drop which through the Capital constraint causes Loans to reduce

2.6.7 Empirical evidence of the Creeping-up Effect

We have tried to examine the existence of the Creeping up effect. For that purpose we have assumed that a Treatment takes effect when banks face negative Rates for different durations. We have tested the hypothesis assuming Treatment takes effect when the duration of NIRP is at least a) 1 year b)2 years c) 3 years d) 4 years e) 5 years . Expectation is that the more years a bank faces NIRP the larger the impact on both Loans and Capital Changes will be. Table 2.19 and 2.20 below show the detrimental effect of a low for long environment which is amplified with an increasing number of years under negative rates. In essence the detrimental effect is larger the higher the duration of NIRP.

Table 2.19:
Evidence of the Creeping-up
Effect on Lending

	Change in Loans for different durations of NIRP (Propensity Score Matched Banks)																	
	Change in Loans (more than 1 years of NIRP)			Change in Loans (more than 2 years of NIRP)			Change in Loans (more than 3 years of NIRP)			Change in Loans (more than 4 years of NIRP)			Change in Loans (more than 5 years of NIRP)			Change in Loans (more than 6 years of NIRP)		
	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value
a(Dates)	-0.005109	0.004270	0.2316	-0.005100	0.004268	0.2321	-0.005084	0.004264	0.2332	-0.005477	0.004254	0.1979	-0.004515	0.004243	0.2873	-0.005692	0.004221	0.1775
$\beta 1$ (Period *Dates)	-0.0004330	0.0004623	0.3490	-0.0004345	0.0004620	0.3471	-0.0004343	0.0004617	0.3469	-0.0003935	0.0004607	0.3932	-0.0004821	0.0004598	0.2945	-0.0003520	0.0004579	0.4422
$\beta 2$ (Treated*Dates)	-0.0008918	0.012887	0.4890	-0.0008983	0.012908	0.4865	-0.0009441	0.013045	0.4693	-0.0004956	0.013314	0.7097	-0.017406	0.013686	0.2035	-0.0003291	0.014796	0.8240
$\beta 3$ (Period * Treated*Dates)	0.375965	0.054568	0.0000	0.453811	0.062761	0.0000	0.458047	0.064063	0.0000	0.531033	0.072676	0.0000	0.545155	0.076560	0.0000	0.639769	0.098997	0.0000
GDP Growth	0.021509	0.001881	0.0000	0.021610	0.001880	0.0000	0.021605	0.001880	0.0000	0.021540	0.001879	0.0000	0.021644	0.001880	0.0000	0.021348	0.001880	0.0000
Inflation	0.003588	0.001505	0.0172	0.003299	0.001510	0.0289	0.003337	0.001510	0.0271	0.003260	0.001508	0.0307	0.003507	0.001507	0.0200	0.003932	0.001497	0.0086
Size	0.000993	0.002023	0.0000	0.000918	0.002036	0.0000	0.0009845	0.002033	0.0000	0.010094	0.002032	0.0000	0.009489	0.002031	0.0000	0.000860	0.001998	0.0000
Number of Banks	630			630			630			630			630			630		
R-squared	0.034541			0.035386			0.035167			0.035620			0.035098			0.033471		

Notes:

Table show the detrimental effect in Lending of a low for long environment which is amplified with an increasing number of years under negative rates

Table 2.20:
Evidence of the Creeping-up
Effect on Tier1 Capital

	Change in Tier1 Capital for different durations of NIRP (Propensity Score Matched Banks)																	
	Change in Tier1 Capital (more than 1 years of NIRP)			Change in Tier1 Capital (more than 2 years of NIRP)			Change in Tier1 Capital (more than 3 years of NIRP)			Change in Tier1 Capital (more than 4 years of NIRP)			Change in Tier1 Capital (more than 5 years of NIRP)			Change in Tier1 Capital (more than 6 years of NIRP)		
	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value	Coefficient	Std Error	P-Value
a(Δ rates)	0.000222	0.000199	0.2637	0.000222	0.000199	0.2637	0.000223	0.000199	0.2634	0.000224	0.000199	0.2610	0.000222	0.000199	0.2654	0.000227	0.000199	0.2537
$\beta 1$ (Period * Δ rates)	-0.012559	0.002770	0.0000	-0.012543	0.002770	0.0000	-0.012450	0.002769	0.0000	-0.012419	0.002767	0.0000	-0.012375	0.002766	0.0000	-0.012363	0.002766	0.0000
$\beta 2$ (Treated* Δ rates)	-0.018818	0.014529	0.1953	-0.018449	0.014559	0.2051	-0.017316	0.014750	0.2405	-0.013632	0.015110	0.3670	-0.020561	0.015588	0.1872	0.002744	0.017190	0.8732
$\beta 3$ (Period * Treated* Δ rates)	0.194372	0.054404	0.0004	0.204285	0.056977	0.0003	0.244901	0.071352	0.0006	0.347701	0.095640	0.0003	0.474829	0.122852	0.0001	0.599484	0.160009	0.0002
GDP Growth	0.015766	0.002429	0.0000	0.015765	0.002429	0.0000	0.015753	0.002428	0.0000	0.015660	0.002427	0.0000	0.015895	0.002426	0.0000	0.015779	0.002420	0.0000
Inflation	0.013961	0.001582	0.0000	0.013951	0.001582	0.0000	0.013894	0.001585	0.0000	0.013779	0.001587	0.0000	0.013628	0.001590	0.0000	0.013819	0.001585	0.0000
Size	0.017104	0.002567	0.0000	0.017148	0.002568	0.0000	0.017337	0.002572	0.0000	0.017802	0.002580	0.0000	0.017901	0.002592	0.0000	0.018374	0.002558	0.0000
Number of Banks	642			642			642			642			642			642		
R-squared	0.017971			0.017984			0.017858			0.018031			0.018357			0.018139		

Notes:

Table show the detrimental effect in Tier 1 Capital of a low for long environment which is amplified with an increasing number of years under negative rates

2.6.8 Optimal sequencing of QE

One of the most important arguments of the Interest Rate Reversal Theory is that there is only one correct way for central banks to perform Quantitative Easing. Specifically, Asset Purchases remove from financial institutions' balance sheet those securities that generate capital gains and as a result decrease maturity mismatch of their balance sheets. Therefore, the optimal sequence to do Quantitative Easing is to first exhaust Interest Rate cuts and then do Quantitative easing.

In the following graphs (figure 2.21) we can see Asset Purchases from a sample of four central Banks. From the graphs we can observe that while Bank of England and the Swiss SNB had performed important Asset purchases from 2008, this is not the case for the ECB and the Swedish RiskBank which only started Asset purchases during 2014 when the policy rates hit the negative territory.

Empirical Model – Triple Difference in Difference (DDD)

To test which of the above two Central Banks strategies is more favourable we have employed a Triple Difference in Difference (DDD) empirical model. Such a specifications allows to test for two experiments happening at the same time. In our case the first experiment is the introduction of a negative interest rate policy (NIRP) , while the second experiment is whether the central banks have applied the full Quantitative Easing after 2014 (i.e after Rate cuts have gone negative) .

We define 2014 as the year where all countries of our Treated Group have turned to negative interest rates with the period (P) before this the pre experiment period (P=0) and the period from 2014 and onwards the post experiment (P=1) period.

Treated is the variable that takes 1 when the country's central bank has applied a Negative Interest Rate policy

QE is the variable that takes 1 when the country's central bank has not applied significant QE (i.e < 30% of Total Asset Purchases of the period) before 2014 and 0 otherwise. Table 2.22 shows the Total QE that has happened until 2014 as a percentage of the total QE of our sample period (up to 2018).

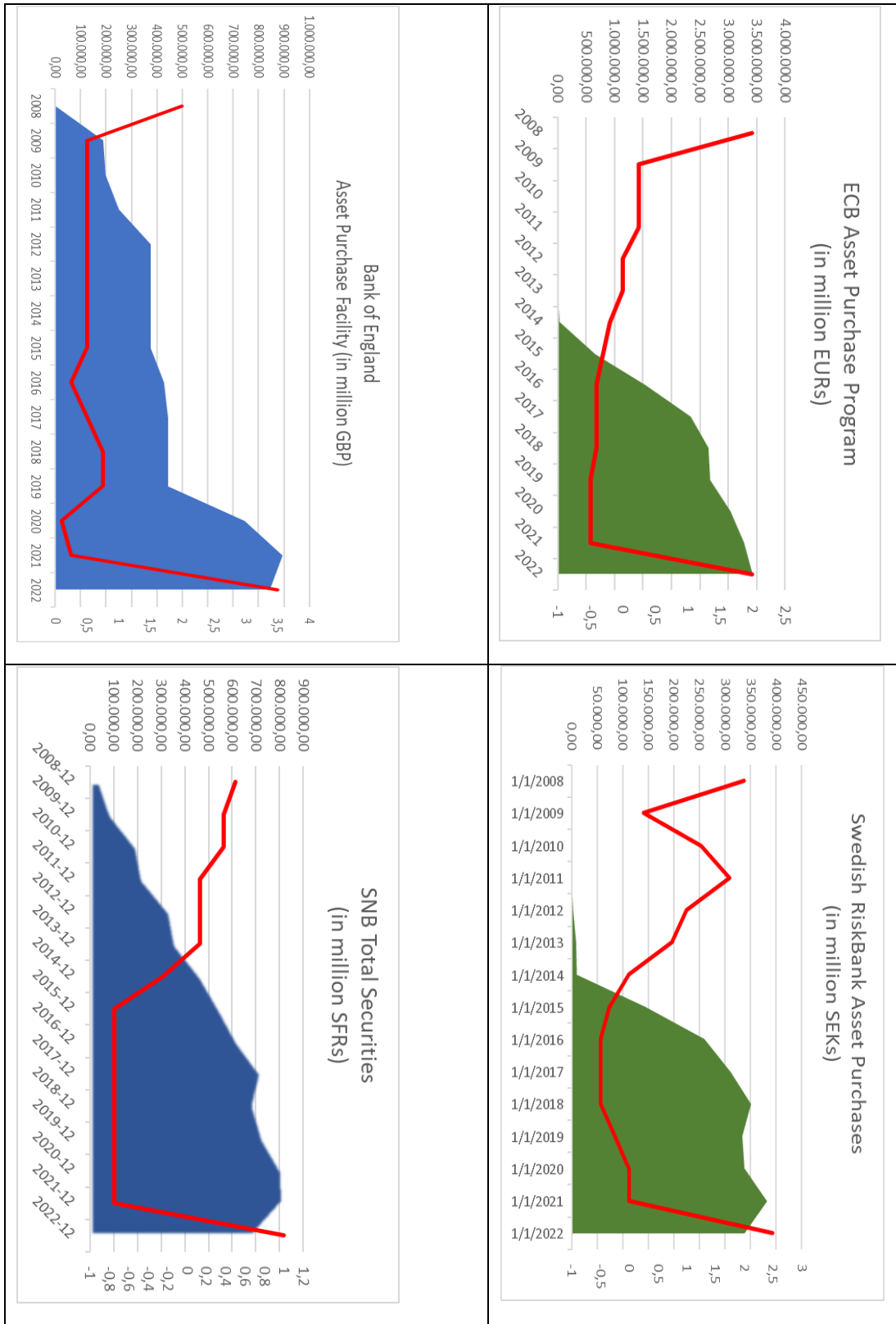
Our DDD empirical specification similar to the model defined by Olden, Moen, Journal of Econometrics (2022) will be the following:

$$Y_{i,j,t} = a + \beta_1 * T + \beta_2 QE + \beta_3 Period + \beta_4 T * QE + \beta_5 T * Period + \beta_6 QE * Period + \beta_7 (T * QE * Period) + e_{ijt}$$

Our coefficient of interest is β_7 which is capturing the effect of the interaction i.e the effect of low interest rates for those banks where the country's central has not applied significant QE before 2014

Figure 2.21:

Asset Purchases of four central Banks



Notes: From the graphs we can observe that while Bank of England and the Swiss SNB had performed important Asset purchases as early as 2008, this is not the case for the ECB and the Swedish RiskBank which only started Asset purchases during 2014

Table 2.22:

Total QE by country

	Percentage of Total QE (Asset Purchases up to 2014 / Asset purchases up to 2018)	QE (<30%)
Norway	0,00%	1
Eurozone	1,19%	1
Sweden	2,96%	1
Argentina	21,34%	1
Turkey	52,48%	0
Switzerland	67,93%	0
Poland	75,74%	0
Russia	75,81%	0
Israel	81,31%	0
Canada	81,72%	0
Iceland	81,97%	0
Australia	83,56%	0
UK	84,33%	0
Denmark	100,00%	0

Notes: Total QE that has happened until 2014 as a percentage of the total QE of our sample period (up to 2018)

In such an empirical specification the conditional Mean can take eight values

- $E(Y | T = 0, QE = 0, \text{Period} = 0) = \alpha$
- $E(Y | T = 1, QE = 0, \text{Period} = 0) = \alpha + \beta_1$
- $E(Y | T = 0, QE = 1, \text{Period} = 0) = \alpha + \beta_2$
- $E(Y | T = 0, QE = 0, \text{Period} = 1) = \alpha + \beta_3$
- $E(Y | T = 1, QE = 1, \text{Period} = 0) = \alpha + \beta_1 + \beta_2 + \beta_4$
- $E(Y | T = 1, QE = 0, \text{Period} = 1) = \alpha + \beta_1 + \beta_3 + \beta_5$
- $E(Y | T = 0, QE = 1, \text{Period} = 1) = \alpha + \beta_2 + \beta_3 + \beta_6$
- $E(Y | T = 1, QE = 1, \text{Period} = 1) = \alpha + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7$

As mentioned earlier, according to Brunnermeier et al when QE precedes Rate cuts, long dated assets from banks' balance sheets are getting replaced with short term reserves. Therefore we expect that banks in countries where QE has happened at a later stage will show higher lending activity compared to banks where QE has happened very early and on larger scale

Empirical results in Table 2.23 show that banks in countries under NIRP, that have only done significant QE from 2014 and onwards show both higher Lending activity and Core Tier 1 capital compared to those banks where QE has happened at the very beginning.

Table 2.23:

Countries under NIRP, that have only done significant QE from 2014 and onwards

QUANTITATIVE EASING (Propensity Score Matched Banks)				
	Total Loans /Total Assets		Core Tier 1 Capital	
	Coefficient	P-Value	Coefficient	P-Value
α	0.520542	0.0000	0.215962	0.0000
Treated	0.146951	0.0000	0.001434	0.8570
β_2 *QE	-0.126105	0.0000	0.003000	0.7896
β_3 *Period	0.218000	0.0000	0.136755	0.0000
β_4 *Treated	0.156229	0.0000	-0.007655	0.5731
β_5 (Treated*Period)	-0.213762	0.0000	-0.149396	0.0000
β_6 (QE*Period)	-0.127273	0.0000	-0.131932	0.0000
β_7 (Period * Treated*QE)	0.118866	0.0002	0.167397	0.0000
GDP Growth	-0.007075	0.0000	-0.000102	0.8853
Inflation	-0.010280	0.0000	0.002905	0.0024
Size	-0.000977	0.7856	-0.031214	0.0000
R-squared	0.211347		0.158288	

Notes: Table shows that banks in countries under NIRP , that have only done significant QE from 2014 and onwards show both higher Lending activity and Core Tier 1 capital compared to those banks where QE has happened at the very beginning.

2.6.9 Robustness Check

In order to check the robustness of our results we have used a different methodology where a) we applied a different outlier detection and correction method b) we used propensity score weighting instead of propensity score matching. Unfortunately, some of the results were found not to be robust using the alternative methodology.

Profitability

Primarily, the impact of NIRP on Net Interest Income was found not to be robust while the impact on Net Interest Expenses continued to be strong and robust

Risk Appetite & Riskiness

Results for Credit and Market RWA's remained strong and robust.

Capital Adequacy

The alternative methodology found no impact on the capital adequacy ratios. This is the case for all proxies: i.e Leverage Ratio, Core Tier 1, and Tier 1 ratios.

Bank Operations

The NIRP effect on Deposits over Assets and Loans over Assets remained strong and robust.

Table 2.24:

Sample Robustness Checks using our alternative methodology

	Robustness Checks (Alternative Methodology)							
	Deposits / Total Assets		Total Loans / Total Assets		Net Interest Income		Credit RWA / Total Assets	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Constant	0,7081	0,00	0,6612	0,00	0,02970	0,00	0,05650	0,58
Period	0,0354	0,60	-0,0397	0,35	0,00320	0,02	0,26110	0,01
Treated	0,2192	0,00	0,2208	0,00	-0,00430	0,00	0,20900	0,00
NIRP	-0,1753	0,00	-0,2134	0,00	0,00200	0,06	-0,22780	0,00
Size	-0,0259	0,15	-0,0017	0,93	-0,00200	0,00	0,02930	0,16
GDP Growth	-0,0206	0,00	-0,0166	0,00	-0,00020	0,29	-0,00440	0,28
Inflation	-0,0094	0,02	-0,0088	0,01	-0,00020	0,07	-0,00340	0,01
R-squared	0,201		0,192		0,06500		0,18400	

Notes: The NIRP effect on Lending, Deposits and Credit RWA remained robust under all methodology specifications. However, the effect on Net Interest Income is not robust which implies that although the Reversal interest Rate effect may exist the mechanism proposed by Brunnermeier et al cannot be proved

Summing up, the results of both our basic and our challenger models reiterate the existence of the reversal interest rate. However, the mechanism proposed by Brunnermeier et al, that this is happening because of the existence of two opposite forces (Net Interest Income vs Capital Gains) affecting the institution's net worth, fails to pass our robustness checks.

Chapter III: The effect of capital ratios on the probability of a Banking crisis and the associated Economic cost

Abstract

In this study we evaluate the effect of Capital Ratios on the likelihood of a Banking Crisis as well as their Economic cost. We found that a one percentage point increase in the regulatory capital ratio decreases the probability of a banking crisis by 4.17%. We believe that Banks pass on to their clients any increase in the Capital Ratios through the mechanism of an increased Lending Spread. We have found a positive and statistically significant relationship of Capital Adequacy Ratio with Lending Spreads. Specifically, a 1% increase in the CAR increases the Lending Spread by 27 Basis points. Other factors that affect Lending Spreads are the ROE and Real Interest Rates. Finally, an increase in the regulatory Capital Ratios also impacts indirectly the GDP per capita, the Financial System Deposits as percentage of GDP and the level of Bank Credit as a percentage of deposits.

3.1 Literature Review

Systemic Banking crises are way more frequent than what most people believe and are usually associated with enormous declines in employment and GDP. Bordo et al. (2001) argue that the frequency of banking crises has doubled in recent decades (i.e since 1973) as a consequence of financial liberalization in the 80s and has now reached the highest level since Great Depression in the 30s.

Carmen M. Reinhart et al, 2009 estimate that for every bank crisis, output declines on average by 9% whereas unemployment increases by 7%. Demirgüç-Kunt et al, 1998 argue that low growth is significantly correlated with increasing banking risks. In addition, high inflation increases the overall risk of the sector. They also argue that a tight monetary policy that can tame inflation is very much desired in order to keep stability of the banking sector.

Beck et al in 2006, assessed the effect of banking concentration on the data of 69 countries for the period of 1980 to 1997. Their analysis showed that banking crises are unlikely to happen in an environment where the financial systems is more concentrated.

Kaminsky et al, 1999 argued that usually a banking crisis precedes a currency crisis. Then the currency crisis will amplify the banking crisis causing a vicious spiral. According to the authors, crises typically happen when the economy has entered a downturn, following a rapid increase in economic activity that was triggered by credit and an overvalued currency.

Similarly, Gavin et al (1996) examined Latin America banking crises and found that rapid increases in lending activity have typically preceded banking crises. Same applies for some industrial countries such as Japan, Finland, Sweden, Norway and the US.

3.2 Empirical Model

3.2.1 Assessing the impact of capital adequacy ratios on the probability of crisis

In this chapter we have tried to assess the effect of capital adequacy ratios on the probability of crisis. We have used the methodology introduced by Demirgüç-Kunt and Detriagiache (IMF Economic Review, 1998). Specifically, we have used a multivariate logit model where the likelihood of a financial crisis is a function of a set of potential explanatory variables.

For every Year the country is either experiencing a crisis and hence the Banking Crisis dummy gets a value of 1 or not and the Banking Crisis dummy gets a value of 0. The probability of a financial crisis occurring at time t for country I is assumed to be a function of a set of n variables $X(it)$. For example, let $P(it)$ be the Banking Crisis dummy which takes a value of 1 or 0, β a vector of coefficients that we are looking to estimate and $F(\beta'X(it))$ the cumulative probability distribution at $\beta'X(it)$. The log-likelihood of the model that will be maximised is (Demirgüç-Kunt and Detriagiache , IMF Economic Review, 1998) :

$$Ln(L) = \sum_{t=1}^T \sum_{i=1}^n \{P_{t,i} \ln [F(\beta'(x_{t,i}))] + (1 - P_{t,i}) \ln [1 - F(\beta'(x_{t,i}))]\}$$

To calculate the maximum likelihood estimates we need to take derivatives of the log likelihood with respect to the parameters and then set the first derivative to zero. Please note that the estimated parameters would show the impact of a change in the correspondent explanatory variable on $\ln(P(it)/(1 - P(it)))$, not on $P(I,t)$.

3.2.2 The dataset

We have built the Banking Crisis dummy using the Global Crisis data published by Harvard Business School:

(<https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx>) .

The data were collected over a number of years by Carmen Reinhart. This dataset of Crisis data is the most complete we are aware and contains Banking Crisis for over 70 countries from 1800 to today, FX rate crisis, stockmarket crisis, debt defaults as well as other data series. In our case we used data from 1988-2016 from 70 countries. An overview of the Crisis across the globe can be found on the Table 3.1.

Table 3.1:

Banking Crisis by Country and year 1988-2016

Country	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	
Algeria			1	1	1																							
Angola					1	1	1	1	1	1	1																	
Argentina		1	1					1	1					1	1	1												
Australia		1	1	1	1																							
Austria																						1	1	1	1			
Belgium																						1	1	1	1	1	1	1
Bolivia								1	1	1			1															
Brazil			1	1			1	1	1	1																		
Burma (Myanmar)										1	1					1	1	1	1									
Central African Republic	1	1	1	1	1	1	1	1	1	1	1	1	1															
China											1	1	1															
Colombia											1	1	1															
Costa Rica	1	1	1	1			1	1	1																			
Denmark	1	1	1	1	1																	1	1	1	1	1	1	1
Dominican Republic										1							1	1										
Ecuador										1	1	1	1	1	1	1												
Egypt			1	1	1	1	1	1	1																			
El Salvador		1	1									1	1															
Finland				1	1	1	1					1	1															
France								1	1													1	1	1	1	1	1	1
Germany																						1	1	1				
Ghana	1	1									1	1	1															
Greece				1	1	1	1	1	1													1	1	1	1	1	1	1
Guatemala			1													1				1								
Honduras													1		1	1												
Hungary				1	1	1	1	1															1	1	1	1	1	1
Iceland																						1	1	1	1	1	1	1
India						1	1	1	1	1	1																	
Indonesia					1		1				1	1	1	1	1	1												
Italy			1	1	1	1	1	1	1													1	1	1	1	1	1	1
Ivory Coast	1	1	1	1																								
Japan					1	1	1	1	1	1	1	1	1	1	1													
Kenya	1				1	1	1	1																				
Malaysia	1										1	1	1	1	1													
Mauritius										1																		
Mexico						1	1	1	1	1																		
Netherlands																						1	1	1	1	1	1	1
New Zealand	1	1	1																									
Nicaragua	1	1	1	1	1	1	1	1	1	1				1	1													
Nigeria						1	1	1	1		1												1	1	1	1	1	1
Norway	1	1	1	1	1	1																						
Panama	1	1																										
Paraguay									1	1	1	1	1			1												
Peru	1	1	1													1												
Philippines											1	1	1	1	1													
Poland				1	1	1	1	1																				
Portugal																						1	1	1	1	1	1	1
Romania			1	1	1	1	1	1	1	1	1	1																
Russia								1			1											1	1	1	1	1	1	1
South Africa		1																										
South Korea	1										1	1	1	1														
Spain																							1	1	1	1	1	1
Sri Lanka		1	1	1	1	1																						
Sweden				1	1	1	1															1	1	1				
Taiwan									1		1	1																
Thailand										1	1	1	1	1														
Tunisia				1	1	1	1	1																				
Turkey					1		1							1	1													
United Kingdom				1					1													1	1	1	1	1	1	1
Uruguay																1	1	1	1									
USA	1	1	1	1																		1	1	1	1			
Venezuela						1	1	1	1															1	1			
Zambia								1	1	1	1																	
Zimbabwe								1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Notes: Source Carmen Reinhart, Harvard business School

3.2.3 Empirical Results

Similar to other works on similar subjects (Wong, 2010, Demirgüç-Kunt et al, 2006), we applied a general-to-specific methodology. The general model contains independent variables such as regulatory capital adequacy ratio, inflation ratio, current account balance as percent of GDP, real interest rate (Bank lending rate minus inflation), NPL as a percentage of the banking sector, Household Debt, year on year GDP growth, lending spread (i.e lending rate minus the deposit rate), Ratio of bank capital and reserves to total assets and the financial system deposits as percent of GDP (according to the database this includes Demand, time and saving deposits in deposit money banks and other financial institutions as a percent of GDP). Our results are reported in Table 3.2 below.

We have progressively reduced our general model 1 (Table 3.2) in order to include only these variables that are statistically significant at the 5 percent level.

Results show that Inflation ratio, Current account balance, Non Performing Loans, Household Debt and Bank capital over Assets are positively correlated with the probability of a banking crisis. In contrast we can see that higher Capital Adequacy ratios are related with a reduced probability of a banking crisis. We can also see that lending spread and real interest rate have a negative sign. High GDP growth, is statistically significant across all specifications and decreases the probability of a banking crisis. Finally, high deposits in the financial system also reduce the probability of a banking crisis. To summarize, CAR, GDP growth, NPLs and Household Debt were found significant in all model specifications

Table 3.2:

General to specific approach for determining regressors of the multivariate Logit model

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
CAPITAL ADEQUACY RATIO	-0,786	0,040	-0,691	0,030	-0,566	0,000	-0,198	0,000	-0,191	0,000	-0,200	0,000	-0,218	0,000
GDP GROWTH	-0,536	0,040	-0,604	0,010	-0,565	0,000	-0,392	0,000	-0,391	0,000	-0,389	0,000	-0,397	0,000
NPL	1,261	0,010	1,474	0,000	1,467	0,000	0,539	0,000	0,535	0,000	0,525	0,000	0,522	0,000
HOUSEHOLD DEBT	0,147	0,030	0,172	0,000	0,168	0,000	0,021	0,000	0,021	0,000	0,021	0,000	0,023	0,000
INFLATION	0,598	0,080	0,542	0,050	0,484	0,060	-0,071	0,490	-0,085	0,390	-0,060	0,520		
DEPOSITIS_OVER_GDP	-0,134	0,060	-0,160	0,010	-0,162	0,010	-0,003	0,760	-0,003	0,730				
CURRENT_ACCOUNT	0,297	0,090	0,292	0,020	0,265	0,020	0,016	0,620						
REAL_INTEREST_RATE	-0,060	0,740	-0,141	0,440	-0,158	0,380								
BANK CAPITAL_OVER_ASSET	0,300	0,440	0,129	0,600										
LENDING SPREAD	-0,064	0,870												

Notes: Table shows that Inflation ratio, Current account balance, NPLs, Household Debt and Bank capital over Assets are positively correlated with the probability of a banking crisis

As mentioned earlier, the estimated parameters would demonstrate the impact of change in the respective explanatory variable on $\ln(P(i_t) / (1 - P(i_t)))$, not on $P(i_t)$. Specifically, our model with the estimated parameter is the following:

$$\ln\left(\frac{P_{i,t}}{1 - P_{i,t}}\right) = -0.218 CAR_{i,t} - 0.397 GDP\ GROWTH_{i,t} + 0.522 NPL_{i,t} + 0.023 HOUSEHOLD\ DEBT_{i,t}$$

After, taking exponentials on both sides and rearranging we have the following format:

$$P_{i,t} = \frac{1}{1 + e^{-(-0.218 CAR_{i,t} - 0.397 GDP\ GROWTH_{i,t} + 0.522 NPL_{i,t} + 0.023 INFLATION_{i,t})}}$$

We can now calculate the impact of a 1% move of each explanatory variable with respect to the actual probability of a Banking Crisis around the mean (Table 3.3)

Table 3.3:

Effect of independent variables on the probability of banking crisis

Period (1988-2016)	Mean	Impact on P after increase of 1% in the explanatory Variable
CAR	14.77%	-4.1736%
GDP GROWTH	3.43%	-7.2650%
NPL	4.78%	11.5847%
HOUSEHOLD DEBT	49.61%	0.4656%

Notes: Estimation of the Impact on the Probability of a Banking Crisis after an increase of 1% around the mean

Table 3.4:

Estimated Probabilities of Banking Crisis by country

Country	Economic growth: the rate of change of real GDP	Household debt to GDP, in percent	Banking system regulatory capital to risk-weighted assets	NPL	Probability of Banking Crisis
Russia	1,63	15,8	12,07	10	90,93%
India	7,17	10,8	12,82	9,98	45,43%
Spain	2,89	61	15,55	4,46	30,87%
Australia	2,37	120,9	14,55	0,89	29,58%
Denmark	2,04	116,5	21,71	2,29	15,87%
USA	2,22	77,6	14,53	1,13	15,79%
Ireland	8,15	46,8	25,34	11,46	15,43%
Colombia	1,35	26,97	18,63	4,18	14,25%
Canada	2,98	100,4	14,81	0,45	13,38%
Brazil	1,06	27,3	18,15	3,59	13,29%
Belgium	1,96	60,3	18,96	2,92	11,92%
France	2,26	58,5	18,91	3,08	11,24%
Netherlands	2,91	107	22,03	2,31	9,19%
Thailand	4,02	68,8	17,95	3,07	8,91%
Austria	2,48	49,5	18,24	2,37	7,01%

Notes: Estimation of the probability of a banking Crisis using model 7 (2017). Russia shows the highest probability of a banking crisis due to high NPL ratios, lower Capital adequacy ratios and small economic growth

3.3 Evaluating the Economic cost of increased capital adequacy ratios

At this stage we have tried to respond on the question regarding the effect of capital adequacy ratios in the Economy. To evaluate this, we make the assumption that any regulatory requirement or any bank decision to increase the capital adequacy ratios is most probably going to impose extra costs on the economy as the financial institutions will try to transfer to their clients an elevated cost of funding through the mechanism of an increasing Lending Spread. As a result, the financial intermediation higher cost would most probably decrease the level of both investment and consumption within the economy, which will be evident if we look the GDP per capita.

To test this assumption, we have simultaneously estimated a system of regression models through an SUR (Seemingly Unrelated Regressions). For the first regression and as mentioned earlier we believe that financial institutions pass any cost related to higher capital adequacy ratios to their clients. As a result, we estimated the effect of capital adequacy ratios on lending spread. By Lending spread we imply loan rate minus the deposit rate. The loan rate is the rate requested by institutions to lend the private sector whereas the deposit rate is the rate depositors are offered by retail institutions on deposits that last 3 months.

3.3.1 The SUR system:

Zellner (1962) on his study proves that when contemporaneous correlation is present, the simultaneously estimated regressions (such as the SUR) method are more efficient compared to independent equation models. This is due to the fact that independent equations solution methodology like the one used under multiple regression may be prone to simultaneous bias. The Zellner's method

(i.e SUR methodology), estimates the coefficient of the system of equations, taking into account both contemporaneous correlation and heteroskedasticity in the residuals across the system.

$$LS_{i,t} = \beta_0 + \beta_1 CAR_{i,t} + \beta_2 ROE_{i,t} + \beta_3 Real\ Interest\ Rate_{i,t} + \varepsilon_{i,t}$$

$$GDP_{percapita}_{i,t} = \gamma_0 + \gamma_1 LS_{i,t-1} + \varepsilon_{i,t}$$

$$Financial\ System\ Deposits_{i,t} = \gamma_0 + \gamma_1 LS_{i,t-1} + \varepsilon_{i,t}$$

$$Bank\ Credit\ as\ percentage\ of\ Deposits_{i,t} = \gamma_0 + \gamma_1 LS_{i,t-1} + \varepsilon_{i,t}$$

The system regression estimates the effect of lending spreads on

a) GDP per capita denoted in the database as “*GDP per capita is gross domestic product divided by midyear population.*”

b) Financial System Deposits as percentage of the GDP denoted in the database as “*Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP*”

c) Bank Credit as percentage of Deposits denoted in the database as “*The financial resources provided to the private sector by domestic money banks as a share of total deposits. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. Total deposits include demand, time and saving deposits in deposit money banks.*”

(Macro Database source: www.theglobaleconomy.com)

According to the literature the best methodology to estimate simultaneously multiple regressions is the SUR methodology. Using SUR we tackle the issue of contemporaneous correlation of the residuals and the resulting estimates of the parameters are more efficient compared to just running OLS on both models.

Table 3.5:

The SUR system to assess the simultaneous impact of lending spreads on GDP per capita, Financial System Deposits and Bank Credit as percentage of Deposits

System: SUR				
Estimation Method: Seemingly Unrelated Regression				
Sample: 1989 2016				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-2.199070	0.809210	-2.717552	0.0066
C(2)	0.263639	0.053016	4.972864	0.0000
C(3)	0.064725	0.012489	5.182464	0.0000
C(4)	0.659212	0.017436	37.80693	0.0000
C(5)	15535.35	503.7463	30.83963	0.0000
C(6)	-425.7859	40.55230	-10.49967	0.0000
C(7)	56.87256	1.188051	47.87047	0.0000
C(8)	-1.074010	0.094776	-11.33214	0.0000
C(9)	111.9581	1.620118	69.10491	0.0000
C(10)	-0.905418	0.129150	-7.010591	0.0000
Determinant residual covariance		6.00E+15		
Equation: LENDING_SPREAD = C(1) + C(2)*CAR + C(3)*ROE + C(4) *REAL_INTEREST_RATE				
Observations: 641				
R-squared	0.696728	Mean dependent var	7.278190	
Adjusted R-squared	0.695299	S.D. dependent var	7.567712	
S.E. of regression	4.177355	Sum squared resid	11115.84	
Durbin-Watson stat	0.819877			
Equation: GDP_PERCAPITA = C(5) + C(6)*LENDING_SPREAD(-1)				
Observations: 1406				
R-squared	0.071751	Mean dependent var	12055.19	
Adjusted R-squared	0.071090	S.D. dependent var	15226.32	
S.E. of regression	14675.13	Sum squared resid	3.02E+11	
Durbin-Watson stat	0.035058			
Equation: FINANCIAL_SYSTEM_DEPOSIT = C(7) + C(8) *LENDING_SPREAD(-1)				
Observations: 1383				
R-squared	0.085678	Mean dependent var	47.66706	
Adjusted R-squared	0.085016	S.D. dependent var	35.78525	
S.E. of regression	34.23031	Sum squared resid	1618137.	
Durbin-Watson stat	0.035221			
Equation: BANK_CREDIT_PERCENT_OF_D = C(9) + C(10) *LENDING_SPREAD(-1)				
Observations: 1375				
R-squared	0.033269	Mean dependent var	104.1926	
Adjusted R-squared	0.032565	S.D. dependent var	46.93793	
S.E. of regression	46.16734	Sum squared resid	2926445.	
Durbin-Watson stat	0.056313			

Notes: Capital Adequacy Ratio, ROE and Real Interest Rate have a positive and statistically significant relationship with Lending Spreads. Lending Spreads have a significantly negative

relationship with GDP per capita, the level of deposits in the financial system and Bank Credit as percentage of deposits

From the results (Table 3.5) of the first regression we can see that Capital Adequacy Ratio has a positive and statistically significant relationship with Lending Spreads (L.S). Specifically, a 1% increase in the CAR increases the Lending Spread by 27 Basis points (0.27%). Similarly, we can see that ROE has a positive and statistically significant relationship with Lending Spread. A 1% increase in the ROE increases the L.S by 6.4 bps (0.064%). Real interest Rate has also a strong positive statistical significance. A 1% increase in the Real Interest Rate increases L.S by 65 bps (0.65%). The R² of the model is 69.67%.

From the results of the remaining regressions (Table 3.5) we can see that Lending Spreads have a significantly negative relationship with GDP per capita. Specifically, a 1% increase in the LS reduces the GDP per capita by 425 dollars. Lending Spreads also have a significantly negative relationship with the level of deposits in the financial system. Specifically, a 1% increase in the LS reduces the Deposits by 1.07%. Finally, Lending Spreads have a significantly negative relationship with Bank Credit as percentage of deposits. Specifically, a 1% increase in the LS reduces the Deposits by 0.90%. Table 3.6 below, summarizes the costs and benefits from an increase in the Capital Adequacy Ratios in our sample

Table 3.6:

Economic cost of increased capital adequacy requirements

CAR increase	Probability of Banking crisis (%)	Change in Lending Spread (bps)	Change in GDP per capita (in \$)	Change in Financial System Deposits % of GDP (in bps)	Change in Bank Credit as % of Deposits (in bps)
1%	-4.17%	27	-114.75	-29	-24

Notes: Summary of the Impact of CAR increase on Profitability, Lending Spreads, GDP per capita, Financial System Deposits and Bank Credit

3.3.2 Crisis After Math: Economic Policies that speed up Economic recovery

In table 3.7 below we can see 38 Banking Crisis since 1980, the columns in the table demonstrate various characteristics of the specific crisis. Specifically % Change Peak-to-trough describes the maximum percentage drop in GDP since the beginning of the crisis, the next two columns years Peak-to-recovery and years Peak-to-trough show the number of years it took for the Economy to reach the pre-crisis level and the number of years it took to reach the lowest GDP level respectively. Finally, Severity index is a calculated index introduced by Reinhart et al in their famous article published in American Economic Review in order to rank the severity of various systemic crisis.

Table 3.7:

Bank Crisis by Country and year.

38 Systemic banking crises								
Year	Country	% change Peak to trough	Number of years		Severity index	Advanced dummy	Double dip dummy	
			Peak to trough	Peak to recovery				
1	1980	Argentina	-21,8	11	18	39,8	0	1
2	1983	Peru	-32,0	11	25	57,0	0	1
3	1981	Philippines	-18,8	3	21	39,8	0	1
4	1994	Venezuela	-24,2	11	14	38,2	0	1
5	2008	Greece	-24,0	6	12	36,0	1	0
6	1981	Mexico	-14,1	7	17	31,1	0	1
7	2001	Argentina	-20,9	4	8	28,9	0	0
8	1980	Chile	-18,9	2	8	26,9	0	0
9	2002	Uruguay	-18,9	4	8	26,9	0	0
10	2007	Ireland	-12,9	3	12	24,9	1	1
11	2008	Italy	-11,3	6	12	23,3	1	1
12	2007	Iceland	-12,2	3	11	23,2	1	0
13	1997	Indonesia	-15,1	2	8	23,1	0	0
14	2008	Ukraine	-14,4	1	8	22,4	0	0
15	2008	Spain	-8,4	6	12	20,4	1	0
16	1991	Finland	-11,8	4	8	19,8	1	0
17	1996	Thailand	-13,6	2	6	19,6	0	0
18	2008	Portugal	-7,2	6	12	19,2	1	1
19	1992	Japan	-2,7	2	6	8,7	1	0
20	2007	United Kingdom	-7,1	2	11	18,1	1	1
21	1990	Brazil	-9,2	5	8	17,2	0	1
22	2008	Netherlands	-5,8	5	10	15,8	1	1
23	1997	Malaysia	-9,8	1	6	15,8	0	1
24	2008	France	-4,3	2	9	13,3	1	1
25	2001	Turkey	-7,3	3	5	12,3	0	1
26	1998	Colombia	-6,0	2	6	12,0	0	0
27	1991	Sweden	-6,2	3	5	11,2	1	0
28	2007	USA	-4,8	2	6	10,8	1	0
29	1994	Mexico	-7,7	1	3	10,7	0	0
30	1985	Malaysia	-4,7	2	4	8,7	0	0
31	1997	South Korea	-6,4	1	2	8,4	1	0
32	2008	Germany	-4,8	1	3	7,8	1	0
33	1998	Russia	-5,2	1	2	7,2	0	0
34	1997	Philippines	-2,7	1	3	5,7	0	0
35	1987	Norway	-0,6	1	3	3,6	1	0
36	1992	Japan	-0,1	1	2	2,1	1	0
37	1983	Thailand	0,0	0	0	0,0	0	0
38	1982	Turkey	0,0	0	0	0,0	0	0

Notes: Number of years “Peak to trough” and number of years “Peak to recovery” for every crisis - Source: Carmen M. Reinhart and Kenneth S. Rogoff

By analysing these Banking Crisis, we have tried to identify those Economic policies that are beneficial for a fast Economic recovery. We have used a simple OLS model where the years from Peak to Recovery variable was used as the dependent variable. The most important policies that we tried to investigate are a) the effect of increased Bank Credit to the Private Sector b) Labor Freedom Changes c) Tightening of the Fiscal Balance by the government d) Policies against inflation e) policies targeting household consumption and f) Investments.

Out of these policies only two were found to be effective in reducing the years it took the economies to recover. Specifically, both increased Bank Credit to the Private Sector and Labor Freedom Changes, were found to be statistically significant with a negative sign

The above results imply that the most efficient way to expedite the recovery of the economy is to a) promote those policies that increase credit to the private sector and hence will allow the economy to expand further b) improve competitiveness of the labour market by imposing those reforms that will promote Labor freedom making the country more attractive and friendly to investors.

Table 3.8:

Impact of different economic policies in the speed of economic recovery

Dependent Variable: YEARS_PEAK_TO_RECOVERY

Method: Least Squares

Date: 02/01/23 Time: 14:34

Sample: 1 38

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.921612	0.945668	3.089469	0.0043
YEARS_PEAK_TO_TROUGH	1.396469	0.242523	5.758081	0.0000

D_BANK_CREDIT_TO_THE_P RI	-0.049110	0.016288	-3.015138	0.0052
D_LABOR_FREEDOM_INDEX __0	-0.153158	0.063491	-2.412265	0.0222
D_FISCAL_BALANCE__PERC EN	0.215208	0.101464	2.121020	0.0423
D_INFLATION__PERCENT_C HA	0.001525	0.000511	2.982342	0.0056
D_HOUSEHOLD_CONSUMPTI ON	0.388336	0.217121	1.788569	0.0838
P_CAPITAL_INVESTMENT__ BI	0.230663	0.417978	0.551854	0.5851
<hr/>				
R-squared	0.787708	Mean dependent var	8.263158	
Adjusted R-squared	0.738173	S.D. dependent var	5.612169	
S.E. of regression	2.871691	Akaike info criterion	5.132343	
Sum squared resid	247.3983	Schwarz criterion	5.477098	
Log likelihood	-89.51452	Hannan-Quinn criter.	5.255004	
F-statistic	15.90212	Durbin-Watson stat	1.755586	
Prob(F-statistic)	0.000000	Wald F-statistic	16.45607	
Prob(Wald F-statistic)	0.000000			
<hr/>				

Notes: Table shows the most efficient policies that can expedite the recovery of the economy: i.e policies that increase credit to the private sector and policies that improve competitiveness of the labour market by promoting Labor freedom making the country more attractive and friendly to investors.

4. Conclusion

Chapter I, was inspired from the discussion around cyclicity of capital requirements and if banks are indeed proactive and have forward looking approach when managing their capital buffers. In this context, the work from Ayuso, Perez and Saurina, 2004 triggered the introduction of the countercyclical buffer in the Basel regulation. According to the proposed theoretical model the authors had to include proxies for all three types of costs (i.e Adjustment costs, Failure costs and costs for Renumerating capital). While Ayuso et al were able to identify the negative correlation between capital buffers and the business cycle for a group of Spanish Banks, their research was not able to adequately explain why cost of failures showed a negative sign. In reality someone would have expected that banks expecting an increase in their NPLs (and hence risks) of their balance sheets, would have increased capital buffers to avoid bankruptcy.

From our side, we have extended this work to cover more than 600 European Banks and while trying to correct the aforementioned misalignment we have also found a statistically negative relationship between the GDP growth and the Capital buffer size which is evidence of cyclicity of the capital buffers. We have also used Risk Weighted Asset density as a better proxy for the risk profile of the banks compared to Non-performing Loans that was widely used in earlier researches. RWAs, which by construction are in the denominator of

Capital Adequacy Ratios, were found to have a positive sign which is evidence of the forward-looking approach and active management of capital buffers followed by Financial Institutions. This result is a strong argument that the Basel III “countercyclical buffer” is not really required given banks will, in any case, actively manage and increase their capital buffers upon expectation of increased risks in their balance sheets.

As an additional policy implication, we suggest that RWA density should be included as an additional indicator for determining GSIBs extra capital buffer requirement. Expectation is that such an approach will penalize those institutions with higher risk exposures, instead of those institutions that may just have big Asset size regardless of how well hedged their risks may be. To ensure a level playing field for this comparison we further suggest that the calculation of the RWA density for the purpose of determining GSIBs is done using the standardized approach which, is mandatory according to Basel III as part of the output floor calculation.

In Chapter II, inspired by the breadth of unconventional monetary policies introduced by central banks during the recent crisis, we have assessed the impact of Negative Interest Rate policies on Profitability, Lending, Riskiness and Capital Adequacy. We have applied a DiD methodology where the treatment is the introduction of negative interest rates. Using our base methodology, our results show that Lending has reduced by 19% compared to the control group of banks that have not experienced negative policy rates which is a strong indication of the “reversal interest rate” effect. We can see similar picture on Net Interest Income and Core tier 1 capital that have both reduced compared to the control Group. However, these later two results were not robust under all methodology specifications, implying that the mechanism proposed by Brunnermeier et al (AER 2023), that the reversal interest rate effect is happening because of the existence of two opposite forces (Net Interest Income vs Capital Gains) affecting the institution’s net worth, fails to pass our robustness check. In addition, we were also able to identify what the literature calls “Creeping-up

effect” where the reduction in Lending becomes even more detrimental when interest rates remain low for long period. With respect to Quantitative Easing , the most optimal sequence is for Central Banks to first do rate cuts and then Asset purchases. This is because Asset Purchase programs remove from financial institutions’ balance sheet those securities that generate capital gains and as a result decrease maturity mismatch of their balance sheets.

Finally, in Chapter III, we tried to answer a set of interlinked questions. The first question is the impact of capital adequacy ratios on the probability of a banking crisis. To assess this, we have used a multivariate logit model where the probability of a financial crisis is a function of a vector of potential explanatory variables both macroeconomic and bank specific. Our results indicate that a 1% increase in the Capital Adequacy ratios reduced the probability of a new Banking crisis by approximately 4.17% In the second question we examined the impact of capital adequacy regulations in the Economic Output and overall Credit provided by Banks. We assumed that any additional regulatory capital requirement to increase the capital is going to impose costs on the economy as the financial intermediaries will try to transfer to customers a higher cost of funding through the mechanism of an increased Lending Spread. Using an SUR model, we found that a 1% increase in the CAR increases the Lending Spread by 27 Basis points which in turn has a detrimental effect on Deposits, Total Credit and GDP per capita. Finally, we examined those economic policies that expedite economic recovery and it appears that the most efficient policies are a) policies that aim to increase credit to the private sector and hence will allow the economy to expand further b) policies that improve competitiveness of the labour market by imposing such reforms that promote Labor freedom making the country more attractive and friendly to investors.

5. Appendix

Estimation Methodology Overview:

Method of Moments (MM)

We remind that according to the classical linear regression

$$y_t = x'_t \beta + \varepsilon_t$$

Where $x'_t = (x_{1t}, x_{2t} \dots \dots x_{kt})$ is a k-vector of explanatory variables, β is a k-vector of regression coefficients and ε_t are the residuals.

The moment conditions under the classical linear regression are:

- 1) $Var[\varepsilon_t] = \sigma^2$, constant across t
- 2) $E[(y_t - x'_t \beta)x_t] = E[\varepsilon_t x_t] = 0$ across t
- 3) $E[\varepsilon_t \varepsilon_s] = 0$ for $t \neq s$

Assuming a sample with T observations the second moment condition becomes

$\frac{1}{T} \sum_1^T (y_t - x'_t \hat{\beta}) x_t = X'Y - (X'X)\hat{\beta} = 0$ solving for $\hat{\beta}$ the MM estimator is equal to

$$\hat{\beta} = (X'X)^{-1} X'Y \text{ which is the same result with OLS}$$

In essence with the Method of Moments we calculate one of the population Moments and then we replace it with the sample equivalent moment. We then solve the equation for the unknown parameter.

Generalised Method of Moments (GMM)

Let's assume now that we have a sample that we believe it is drawn from a Poisson distribution. The first two sample raw moments are given by the following equations:

$$4) \mu = \frac{1}{T} \sum_1^T x_i$$

$$5) \mu_2 = \frac{1}{T} \sum_1^T (x_i^2)$$

The population raw moments of the Poisson distribution are proved by Dobinski to be

$$6) E(x) = \lambda$$

$$7) E(x^2) = \lambda^2 + \lambda$$

Rearranging 6 and 7 we get the Population Moment Conditions of the Poisson Distribution

$$8) E(x) - \lambda = 0$$

$$9) E(x^2) - \lambda^2 - \lambda = 0$$

Similar to the methodology followed in the MM we replace the population moments with the sample moments (equation 4 and 5) calculated from our sample:

$$\begin{bmatrix} \frac{1}{T} \sum_1^T x_i - \hat{\lambda} \\ \frac{1}{T} \sum_1^T (x_i^2) - \hat{\lambda}^2 - \hat{\lambda} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

It turns out that we have two equations with one unknown, therefore the solution for the parameter λ is not unique.

It still possible to use one of the moment conditions to estimate the unknown parameter λ , however by dismissing the $q-p > 0$ (where q : number of moment conditions and p : number of unknown parameters) additional moment conditions we are going to lose valuable information for the population distribution. To tackle this problem the nobel laureate Lars Peter Hansen (1982) in his famous paper ‘‘ Large Sample Properties of Generalized Method of Moments Estimators’’, published in *Econometrica*, introduced the concept of Generalised Method of Moments.

The idea of this paper is that when it’s not possible to solve the equations system, we can still get a good estimate of $\hat{\lambda}$ that brings simultaneously all

sample moment conditions as close to zero as possible. To do this, Hansen defined the following criterion function:

$$Q_T(\lambda) = f_T(\lambda)'W_T f_T(\lambda)$$

Where $f_T(\lambda)$ is the vector of sample moments and W a positive definite weighting matrix

Hansen then proved that the GMM estimator is given by minimising the criterion function:

$$\hat{\lambda} = \arg \min_{\lambda} Q_T(\lambda)$$

Under suitable conditions and with any choice of weighting matrix W it can be proved that this estimator is consistent² and asymptotically normal³.

The variance of such an estimator will be

$$V_{GMM} = (G^T W G)^{-1} G^T W \Omega W^T G (G^T W^T G)^{-1}$$

Where the Jacobean $G = E[\nabla f_T(\lambda)] = \begin{bmatrix} \frac{\partial f_1(\lambda)}{\partial \lambda_1} & \dots & \frac{\partial f_1(\lambda)}{\partial \lambda_p} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_q(\lambda)}{\partial \lambda_1} & \dots & \frac{\partial f_q(\lambda)}{\partial \lambda_p} \end{bmatrix}$ for q moment

conditions and p unknown parameters and the variance covariance matrix $\Omega = E[f_T(\lambda)f_T(\lambda)']$

² Consistency is the property of an estimator where having sufficient number of observations, the estimator converges in probability to the true value of parameter

³ Asymptotic normality is the property that allows us to construct confidence bands for the estimator and perform statistical tests

However only , with the right choice of the weighting matrix W the estimator is asymptotically efficient. It can be proved that the choice of weighting matrix W that gives the smallest possible variance is $W = \Omega^{-1}$ ⁴ and then the variance of the estimator becomes

$$V_{GMM,optimal} = (G^T \Omega^{-1} G)^{-1}$$

Proof for efficiency: Below we are considering the difference between the asymptotic variance with arbitrary weighting matrix W and the asymptotic variance with $W = \Omega^{-1}$

$$\begin{aligned} V(W) - V(\Omega^{-1}) &= (G^T W G)^{-1} G^T W \Omega W G (G^T W G)^{-1} - (G^T \Omega^{-1} G)^{-1} \\ &= (G^T W G)^{-1} \left(G^T W \Omega W G - G^T W G (G^T \Omega^{-1} G)^{-1} G^T W G \right) (G^T W G)^{-1} \\ &= (G^T W G)^{-1} G^T W \Omega^{1/2} \left(I - \Omega^{-1/2} G (G^T \Omega^{-1} G)^{-1} G^T \Omega^{-1/2} \right) \Omega^{1/2} W G (G^T W G)^{-1} \\ &= A(I - B)A^T, \end{aligned}$$

We can see that matrix B is both symmetric⁵ and idempotent⁶ therefore

$$\begin{aligned} A(I - B)A^T &= A(I - B)(I - B)A^T = A(I - B)(I - B)^T A^T \\ &= [A(I - B)][A(I - B)]^T \geq 0 \end{aligned}$$

From the properties of matrix algebra every matrix that multiplied by its transpose is positive semidefinite

⁴ Substituting W with Ω^{-1} $V_{GMM} = (G^T \Omega^{-1} G)^{-1} G^T \Omega^{-1} \Omega (\Omega^{-1})^T G (G^T (\Omega^{-1})^T G)^{-1} = (G^T \Omega^{-1} G)^{-1} \underbrace{G^T (\Omega^{-1})^T G}_{= (G^T (\Omega^{-1})^T G)^{-1}} (G^T (\Omega^{-1})^T G)^{-1} = (G^T \Omega^{-1} G)^{-1}$

⁵ Symmetric is a matrix when $B=B^T$

⁶ Idempotent is a matrix when $B^2=B$

6. References

1. Abadi J, Brunnermeier M., Koby Y., 2023. The Reversal Interest Rate. *American Economic Review*
2. Abuka C., Alinda R., Minoiu C., Peydro J-L., and Presbitero A., 2019. Monetary policy and bank lending in developing countries: Loan applications, rates, and real effects. *Journal of Development Economics*
3. Acharya, S., 1996. Charter value, minimum bank capital requirements and deposit insurance pricing in equilibrium. *Journal of Banking and Finance* 20, 351–375.
4. Arce O., Garcia-Posada M., Mayordomo S., and Ongena S., 2018. Adapting lending policies when negative interest rates hit banks' profits. Banco de España, Documentos de Trabajo
5. Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277–297.
6. Ayuso, J., Perez, D., Saurina, J., 2004. Are capital buffers pro-cyclical? evidence from Spanish panel data. *Journal of Financial Intermediation* 13, 249–264.
7. Basten C., and Mariathasan M., 2018. How banks respond to negative interest rates: Evidence from the Swiss exemption threshold. CESIFO Working Paper 6901-2018, February.
8. Beck, Thorsten, Asli Demirgüç-Kunt, and Ross Levine. 2006 “Bank Concentration, Competition and Crises: First Results.” *Journal of Banking & Finance*
9. Becker S., and Ichino A., 2002. Estimation of average treatment effects based on propensity scores. *The Stata Journal*
10. Benjamin G, Sascha S, and Daniel S., 2019, A capital structure channel of monetary policy. *Journal of Financial Economics*

11. Berger A, Espinosa-Vega M., Frame W., and Miller N., 2005. Debt maturity, risk, and asymmetric information. *Journal of Finance*,
12. Bertrand M., Duflo E., and Mullainathan S., 2004. How much should we trust difference-in-differences estimates? *The Quarterly Journal of Economics*,
13. Black L., and Rosen R., 2016. Monetary policy, loan maturity, and credit availability. *International Journal of Central Banking*, Vol. 12, No. 1, pp. 199-230.
14. Bottero M., Minoiu C., Peydro J-L., Polo A., Presbitero A., and Sette E., 2019. Negative monetary policy rates and portfolio rebalancing: Evidence from Credit Register Data. IMF Working Paper, WP/19/44.
15. Bounou W., 2019. Negative interest rate, bank profitability and risk-taking. OFCE Working Paper, No. 10/2019.
16. Bounou W., 2020. Negative interest rates policy and banks' risk-taking: Empirical evidence. *Economics Letters*
17. Bounou W., and Hubert P., 2020. The channels of banks' responses to negative interest rates. Mimeo.
18. Bounou W., and Mawusi C., 2020. Bank intermediation margin in time of negative interest rate policy. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3495247
19. Brei M., Gambacorta, L., 2014. The leverage ratio over the cycle. *BIS Papers*.
20. Brunnermeier M., Koby Y., 2018. The Reversal Interest Rate. NBER Working Paper
21. Bubeck J., Maddaloni A., and Peydró J.-L., 2020. Negative Monetary Policy Rates and Systemic Banks' Risk-Taking: Evidence from the Euro Area Securities Register. *Journal of Money, Credit and Banking*, forthcoming.
22. Campbell, T.S. (1979): "Optimal investment financing decisions and the value of confidentiality", *Journal of Finance and Quantitative Analysis*, 14, 913-924.
23. Carmen M. Reinhart and Kenneth S. Rogoff . 2009, "The Aftermath of Financial Crises", *American Economic Review*

24. Demirguc-Kunt, A., and E. Detriagiache, 1998, "The Determinants of Banking Crises: Evidence from Developing and Developed Countries , IMF Staff Papers 45(Currently IMF Economic Review)
25. Eggertsson G., Juelsrud R., Summers L., and Wold E., 2019. Negative nominal interest rates and the bank lending channel. Norges Bank Research, Working Paper 4/2019.
26. Estrella, A., 2004. The Cyclical Behaviour of Optimal Bank Capital. *Journal of Banking and Finance* 28, 1469–1498.
27. Gavin, Michael and Hausmann, Ricardo, The Roots of Banking Crises: The Macroeconomic Context (January 1996). IDB WP
28. Gunji Hiroshi, 2018. Did BOJ's negative interest rate policy increase bank lending? RIETI Discussion Paper Series, 18-E-086.
29. Hannoun H. 2015. Ultra-low or negative interest rates: what they mean for financial stability and growth. Remarks at the Eurofi High-level Seminar in Riga. April 22. <https://www.bis.org/speeches/sp150424.pdf>.
30. Heider F., Saidi F. and Schepens G., 2019. Life below zero: Bank lending under negative policy rates. *Review of Financial Studies*, Vol. 32, Issue 10, pp. 3727-3761.
31. Hong H., and Kandrak J., 2018. Pushed past the limit? How Japanese banks reacted to negative interest rates. IMF Working Paper, WP/18/131. Jobst A., and Lin H., 2016.
32. International Monetary Fund. World Economic Outlook (series). Washington DC
33. Jackson, P., 1999. Capital Requirements and Bank Behaviour: The Impact of the Basel Accord. BIS Papers.
34. Jokipii, T., Milne A., 2008. The Cyclical Behaviour of European Bank Capital Buffers *Journal of Banking and Finance* 32, 1440-145.
35. Kaminsky, Graciela, and Carmen Reinhart. 1999. "The Twin Crises: The Causes of Banking and Balance of Payments Problems." *American Economic Review*

36. Lindgren, Carl-Johan, Gillian García and Mathew I. Saal (1996): Bank soundness and macroeconomic policy. Washington: International Monetary Fund.
37. Lopez J., Rose A., and Spiegel M., 2020. Negative interest rate policy (NIRP): Implications for monetary transmission and bank profitability in the euro area. International Monetary Fund Working Paper 16/172,
38. Marcus, A.J. (1984). Deregulation and Bank Financial Policy. *Journal of Banking and Finance* 8, 557–565.
39. McNally, W.J. (1999): “Open market stock repurchase signalling”. *Financial Management*, 28, pp. 55-67.
40. Michael Bordo, Barry Eichengreen, Daniela Klingebiel, Maria Soledad . 2001. “Martinez-Peria Is the crisis problem growing more severe?” *Economic Policy*
41. Milne, A., Whalley, A.E., 2001. Bank Capital Regulation and Incentives for Risk-Taking. SSRN.
42. Milne, A., 2004. The Inventory Perspective on Bank Capital. SSRN: <<http://ssrn.com/abstract=576062>>, August.
43. Molyneux P., Reghezza A., Thornton J., and Xie R., 2020. Did negative interest rates improve bank lending. *Journal of Financial Services Research*, Vol. 57, pp. 51-68.
44. Molyneux P., Reghezza A., and Xie R., 2019. Bank profits and margins in a world of negative rates. *Journal of Banking & Finance*, Vol. 107, 105613.
45. Myers, S.C., Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal Financial Economics*. 13, 187–221.
46. Olden, Moen , 2022. The triple difference estimator. *Journal of Econometrics*. Vol 25, Issue 3, Pages 531–553
47. Reinhart, Carmen, and Kenneth Rogoff. 2008. “Banking Crises: An Equal Opportunity Menace.” National Bureau of Economic Research
48. Reinhart, Carmen, and Kenneth Rogoff. 2009. “This Time Is Different: Eight Centuries of Financial Folly”. Princeton University Press, Princeton

49. Schelling T., and Tobin P., 2018. Negative interest rates, deposit funding and bank lending.mimeo.
50. Stolz, S., Wedow, M., 2011. Banks' regulatory capital buffer and the business cycle: Evidence for Germany. *Journal of Financial Stability* 7, 98-110
51. Sudipto B, Arnoud W. A. Boot and Anjan V. Thakor. 1998 "The Economics of Bank Regulation" *Journal of Money, Credit and Banking*
52. Jokipii T., Milne A. 2008 "The cyclical behaviour of European bank capital buffers" *Journal of Banking and Finance*, vol. 32, issue 8, 1440-1451
53. Jose A. Lopez, Andrew K. Rose and Mark M. Spiegel. 2020. Why have negative nominal interest rates had such a small effect on bank performance? Cross country evidence. *European Economic Review*, Vol. 124, No. 103402.
54. Winter, R.A., 1994. The dynamics of competitive insurance markets. *Journal of Financial Intermediation*