Erling Dahl
Jonas Melby Bråten

Stress Testing Norwegian Banks

A Top-Down Approach

Master's thesis in Financial Economics
Supervisor: Petter Eilif de Lange
Co-supervisor: Per Egil Aamo
May 2023

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

NTNU
Norwegian University of
Science and Technology

Erling Dahl
Jonas Melby Bråten

Stress Testing Norwegian Banks

A Top-Down Approach

Master's thesis in Financial Economics
Supervisor: Petter Eilif de Lange
Co-supervisor: Per Egil Aamo
May 2023

Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

NTNU
Norwegian University of
Science and Technology

Preface

This thesis marks the culmination of our two-year Master of Science program in Financial Economics at the Norwegian University of Science and Technology (NTNU), completed in the spring of 2023.

Our interest in this topic stems from the intricate nature of banking structures and risk management. Throughout our studies on this topic, we have gained extensive insight into the Norwegian banking sector and the challenges it faces. Reflecting on the process of writing this thesis, we acknowledge the difficulties encountered but also appreciate the valuable knowledge we have acquired.

We want to express our sincere gratitude to our supervisors, Associate Professor Petter Eilif De Lange of NTNU, and Per Egil Aamo, Deputy Head of Treasury at SpareBank 1 SMN, for their invaluable guidance throughout this project.

Declaration of Compliance

Both authors of this paper declare that this is independent work according to the exam regulations of the Norwegian University of Science and Technology (NTNU).

Trondheim, May 31st, 2023
Jonas Melby Bråten
Erling Dahl

Abstract

In this study, we stress test the solvency capital of a selection of key Norwegian banks under the current capital adequacy framework dictated by the Basel III accord, effective in the EU as of 2010. Our methodology is built upon scenario design, utilizing historical data from past financial crises and extrapolating comparable growth patterns onto critical macroeconomic variables. We implement two distinct modeling strategies for chosen income statement variables pertaining to a curated selection of prominent Norwegian banks, together with a sensitivity analysis on the banks ability to handle credit losses. The two modeling approaches are Forward Stepwise Regression and Lasso Regression.

The Forward Stepwise Regression model is adept at selecting the most statistically significant predictors in a gradual, step-by-step process. Conversely, the Lasso Regression model excels in managing multicollinearity and high-dimensional data sets, efficiently driving the coefficients of irrelevant variables toward zero. Both models prove advantageous when one is unsure which explanatory variables to include in the final model.

Stress testing key banks, some of which are deemed systemically important, allows us to test the resilience of the Norwegian financial system. The outcomes of our stress scenarios reveal that deficits within Norwegian banks occur infrequently. However, in the rare instances when they do materialize, these banks display robust capitalization, thereby ensuring their resilience in weathering these deficits.

Sammendrag

I denne oppgaven stresstester vi kapitalen til et utvalg nøkkelbanker i Norge under de nåværende kapitaldekningskravene gitt av Basel III rammeverket, som har vært effektiv i EU siden 2010. Metoden vår baseres på et makroscenario, som er designet med historiske tall fra tidligere finanskriser, samt enkelte makroøkonomiske størrelser fra stresstester brukt i Norges Bank. Vi bruker to distinkte modelleringsstrategier i stresstesten, samt en sensitivitetsanalyse på bankenes evne til å tåle utlånstap. Modelleringsstrategiene vi benytter oss av er stegvis lineær regresjon (Forward Stepwise Regression) og lasso regresjon (Least Absolute Shrinkage and Selection Operator).

Den stegvise lineære regresjonen estimerer modellene gjennom å velge de mest statistisk signifikante forklaringsvariablene i en gradvis prosess. Lasso regresjonen estimerer også modellene gjennom variabelseleksjon, hvor variablenes koeffisienter krympes, irrelevante variabler settes derfor til null. Lasso regresjonens evne til å redusere koeffisienter gjør den også fordelaktig i håndtering av multikollinearitet. Begge modelleringsteknikkene er effektive man er usikker på hvilke forklaringsvariabler man skal inkludere i en modell.

Stresstesting av nøkkelbanker, hvorav noen er systemkritiske banker, lar oss teste motstandsdyktigheten i det norske finansielle systemet. Resultatene fra våre stresstester gjenspeiler at underskudd for norske banker forekommer sjeldent. De få gangene det faktisk skjer, viser de aktuelle bankene at de er robust kapitalisert, noe som øker evnen til å tåle store underskudd.

Table of Contents

List of Figures

List of Tables

1 Introduction

Banks, as the primary intermediaries of credit, play a crucial role in maintaining financial stability and promoting economic growth. They act as a lender of last resort, provide financing, facilitate saving, and distribute risk evenly in the economy. All of these services tend to weaken in the event of an economic shock, and the governance of the banking sector is an essential step in controlling the build-up of systemic risk. The global financial crisis of 2007-2009 highlighted the need for a more robust approach to assessing the financial sector's resilience in the face of adverse economic shocks. The crisis exposed the vulnerabilities of many banks, which had far-reaching consequences for the global economy. In response, regulators and policymakers have sought to enhance the risk management framework for banks, with stress testing emerging as a vital tool to gauge their ability to withstand financial shocks. A stress test, which is defined by Baudino et al. 2018 as a simulation exercise conducted to assess the resilience to a hypothetical scenario of either a single bank or the system as a whole, was first introduced by Norges Bank (Central Bank of Norway) in the Financial Stability Report of 2004 following the introduction of the Basel II accord. It is now an annual exercise as a part of the oversight of the financial system in Norway.

Financial crisis and economic downturns are, unfortunately, reoccurring events. In its latest report on financial stability, the Central Bank of Norway highlights the substantial uncertainty of the general economic outlook for the coming years. The risk of a downturn has increased due to the geopolitical situation and after-effects of the Covid-19 pandemic. Spillover effects from both Europe and globally represents a massive challenge. High inflation, high interest-rates, and a surge in energy prices have contributed to substantial market volatility. The Central Bank of Norway provides several measures regarding regulations and macroprudential policy to ensure a stable and resilient economy. Financial stability is one of the core objectives for any central bank and policy maker, and in light of recent events regarding Silicon Valley Bank (SVB) and Credit Suisse, it has garnered massive media attention.

On March 8th, SVB released a press statement that it would book a $1.8 billion loss after selling assets to cover increasing withdrawals (SVB Financial Group 2023). Just two days later, on March 10th, the Wall Street Journal headlined the collapse of SVB. In what could be described as a ”bank run”, depositors had attempted to withdraw $42 billion, and Federal Deposit Insurance Corporation (FDIC) announced it had taken control of the bank. This marks by far the biggest bank failure since the near collapse of the financial system of 2008, second only to the failure of Washington Mutual Inc (Choi 2023). As turmoil hits the banking sector and fear spreads across the financial markets, President Biden addresses the world through a televised broadcast to restore confidence in the US banking system. Meanwhile, shares of First Republic and other regional banks' stocks slid as negative news impacted the markets. Through its interconnecting and global structure, it would not take long before the worries about the financial sector spread across the Atlantic. On March 15th, shares of Credit Suisse Group dropped as much as 24%, and other European banks took hits as well, including France's Société Générale and BNP Paribas and Germany's Deutsche Bank. Later that day, it would be announced that the Credit Suisse Group would borrow up to $53,7 billion from the Swiss Central Bank to shore up its liquidity in hopes of regaining investor confidence. This trust was somewhat short-lived, and in an effort by Swiss and global authorities, UBS set out to take over its competitor Credit Suisse. This mega-merger represents a whole new dimension of turmoil in the banking sector, both in America and on the European continent.

The Central Bank of Norway keeps a close eye on the growth of the macroeconomy and the health of the global financial sector. These events may quickly spill over and cause financial instability on Norwegian soil. The Financial Stability Report 2022 highlights key vulnerabilities in the Norwegian financial system and imposes that an increased risk of a downturn implies a greater risk that vulnerabilities materialize (Norges Bank 2022b). Despite these statements, they conclude, through the stress tests, that the financial system is well-equipped to deal with market stress and higher losses. Our goal for this study is to assess a macroprudential Top-down stress test on the Norwegian banking sector. We use a historical scenario design and evaluate this through two alternative modeling approaches and conduct a simple sensitivity exercise on the magnitude of credit losses and their effect on Norwegian banks' capital.

Our research corroborates the assertion made by the Central Bank of Norway, suggesting that the Norwegian financial system exhibits robustness when evaluated through a Top-down stress test. It is essential to acknowledge that the financial sector is continually evolving, and using historical data might not always yield accurate predictions or estimates.

The remainder of this thesis is structured as follows: Section 2 introduces stress testing, its history and functionality in finance, relevant sources of information, and different methods used in practice. Furthermore, we give a brief overview of the Norwegian banking sector and the regulations it must comply with, and how stress testing is used in a regulatory context. Section 3 explains the data extraction, pre-processing, analysis, and limitations of the final data set used for estimating our models. Section 4 provides an insight into the technical development of the models and projection of variables. In contrast, section 5 gives a comprehensive overview of the results from each test and the sensitivity exercise on credit losses and loss of capital. Finally, Section 6 concludes the thesis and provides some final remarks, as well as some ideas for further work.

2 Literature Review

Through this literature review, we seek to provide an overview of stress testing and the history of its usage in finance. We will present the underlying research framework for this paper and showcase the previous methods used in the industry. Finally, we give an overview of the Norwegian banking sector, essential regulations, and how stress testing is used in this context.

2.1 History of Stress Testing and Limitations

The use of stress testing originated in engineering and was traditionally used to test load bearing capacity and stability of a system or structure. Since then, it has been adapted and used in many industries. For example, the medical field uses stress tests to determine how well the heart operates under extreme physical activity. It has been extensively used in software technology as a measure of testing websites and programs beyond the limits of normal operation, and it has become increasingly popular in the field of finance as a tool for risk management (Čihák 2007; Herring and Schuermann 2022). Different industries require different procedures to implement stress testing, and though the scope and nature of tests will vary, the underlying concept and purpose are similar. Das et al. 2022 define a stress test as a test used to assess the ability of an object, person, institution, or system to withstand extreme stress or an adverse event. Financial stress testing involves simulating hypothetical scenarios to measure the impact of economic shocks on a bank's balance sheet, capital adequacy, and liquidity. In the early stages, individual banks mainly ran stress tests for internal risk management purposes (Baudino et al. 2018). However, today, stress tests help regulators, supervisors, and market participants to identify potential weaknesses in the banking system and guide policy actions.

The origins of financial stress testing can be traced back to the early 1990s when banks began small-scale stress tests on their portfolio. However, it was not until the late 1990s and early 2000s that stress testing gained prominence due to the Asian financial crisis and other economic events. In response, the International Monetary Fund (IMF) and the World Bank introduced the Financial Sector Assessment Program (FSAP) in 1999, which incorporated stress testing as an integral component (International Monetary Fund 2023). Even further development was made when Basel II sat a requirement for banks adopting the Internal-Rating-Based (IRB) approach, to conduct stress tests on their credit-risk models. The 2007-2009 global financial crisis highlighted the need for more rigorous and comprehensive stress testing, and in 2009, the U.S. Federal Reserve implemented the Supervisory Capital Assessment Program (SCAP), a large-scale stress test for the 19 largest U.S. banks (FED 2009). The success of SCAP led to the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, which mandated annual stress tests for large banks in the U.S. called the Comprehensive Capital Analysis and Review (CCAR). In Europe, the European Banking Authority (EBA) began conducting stress tests in 2010, leading to the creation of the Single Supervisory Mechanism (SSM) and the European Systemic Risk Board (ESRB) in 2014. These institutions are responsible for coordinating stress tests across the European Union (EU).

Figure 1: *Timeline of key events in the development of stress testing (Dent et al. 2016).*

Modern banks use financial stress testing to identify potential vulnerabilities in their balance sheets, capital adequacy, and liquidity positions. They evaluate the impact of adverse scenarios, such as severe recessions, stock market crashes, and geopolitical events, to determine the potential losses and ensure they have sufficient capital buffers to withstand such shocks. Stress testing also enables banks to develop and implement risk management strategies, including capital planning, asset and liability management, and contingency funding plans. Supervisory authorities use the results of stress tests to guide regulatory and policy actions, such as imposing higher capital requirements, setting limits on risk concentrations, and enhancing risk management practices.

While stress tests have gradually become mainstream, it is important to keep in mind their limitations. Stress test results are vulnerable to many factors, including limitations in data quality and granularity, severity or scope of the scenarios, and model risk – especially in relation to complex methodologies and related assumptions (Baudino et al. 2018). One major limitation is that it relies on a set of predetermined scenarios, which may not capture all potential risks or accurately reflect the complexity of the financial system. This can lead to a false sense of security among banks and regulators. Another weakness is the reliance on banks' internal models, which can be susceptible to manipulation or misrepresentation. The accuracy of stress testing outcomes depends on the quality and integrity of the input data and assumptions used in the models, which can vary across institutions and jurisdictions. Additionally, stress testing is a backward-looking exercise, as it is based on historical data and relationships. Consequently, it may not accurately predict the impact of novel risks or the behavior of market participants during periods of extreme stress. They do not "forecast" future banks' performance but aim to identify the impact on banks of a specific stress scenario, based on a number of given assumptions (Baudino et al. 2018). In conclusion, financial stress testing has evolved significantly since its inception and is now an essential tool for assessing the resilience of banks and the financial system. While it has its limitations, it continues to play a crucial role in promoting financial stability and informing regulatory and policy actions in modern banking.

2.2 Stress Testing - Working Papers and Staff Memo

A significant portion of the research in the field of financial stress testing originates from central banks and other regulatory bodies. In Europe, the Bank for International Settlements (BIS) plays a key role in conducting stress test results through the Basel Committee on Banking Supervision (BCBS) and publishing papers on the subject. Other important contributors to the literature include the European Banking Association (EBA) and the European Central Bank (ECB). In Norway, the majority of models and methods are developed by the Norwegian Central Bank and the Financial Supervisory Authority of Norway.

Working papers from both the EBA and BIS are highly influential in the realm of financial and macroprudential stress testing methodology. Their research forms the foundation for the Basel Accords and serves as an ongoing evaluation of policy actions.

Regarding the Norwegian market, most stress testing methodologies and results are published by the Central Bank of Norway through its reports and staff memos. The Central Bank of Norway has also developed models specifically tailored to the Norwegian economy. We have drawn inspiration from the banking model (Bankmodellen) and analyzed its application in the 2015 Financial Stability Report (Syversten et al. 2015). However, our access to the "Bankmodellen" is limited to qualitative information, and our technical implementation will differ accordingly. Another notable aspect is the use of the highly advanced Norwegian Economy Model (NEMO) by the Norwegian Central Bank in designing macroeconomic scenarios. Unfortunately, we do not have access to a macro-model for use in our stress scenarios. As a result, our scenarios are less sophisticated in nature.

2.3 Overview of Methods Used in Stress Testing

Two main categories of stress testing approaches exist, Top-down and Bottom-up. These approaches differ in terms of who conducts the test, which variables that are stressed, data requirements, and the outcomes that want to be tested. Regulatory authorities usually carry out Top-down stress tests to assess how individual banks or banks on an aggregated level can withstand severe macroeconomic shocks while maintaining solvency. Methods used for examining how stress scenarios affect banks in a Top-down approach are typically based on publicly available data with a relatively low degree of granularity. This limits the ability to make detailed estimates of individual banks' portfolios and their performance during a crisis. Models developed may also be less precise. Top-down approaches are advantageous for comparing effects across different banks and require less intensive data processing. The supervisory Top-down model has been criticized for being opaque and discouraging the bank's own risk management (Casellina et al. 2020). In contrast, Bottom-up stress testing approaches are performed mainly by individual firms, utilizing information and data specific to their own portfolio, resulting in a more granular basis for model estimation. A Bottom-up stress test typically breaks down an individual portfolio into smaller subsets and tests how these subsets perform under potentially severe scenarios suggested by the firm itself or imposed by authorities. There is less relevance to comparing outcomes of Bottom-up stress testing across firms. When banks estimate their own models, there is a risk that they are too conservative; banks may have incentives to underestimate the impact of a shock to reduce supervisory reaction (Casellina et al. 2020).

The policy objectives of stress testing differ based on whether the test is macroprudential or microprudential. A macroprudential stress test is used to evaluate the resilience of the financial system as a whole to economic and financial shocks. In contrast, a microprudential stress test is designed to assess the resilience of individual banks to such shocks (Baudino et al. 2018). Top-down approaches are more suitable for macroprudential stress testing, while Bottom-up approaches are better suited for microprudential stress testing. Another crucial aspect of stress testing exercises is whether balance sheet projections are dynamic or static. Dynamic balance sheet projections allow for elements and characteristics of a bank's balance sheet to vary over the stress testing period. Thus, they are more appropriate for macroprudential exercises where a bank's risk profile can vary throughout the scenario (Baudino et al. 2018). This is a realistic assumption, given that banks most likely will recapitalize and reduce their risk exposure during a crisis. In addition, more realistic assumptions regarding customer behavior, especially for deposits during stress are important. We see that there are discussions among the regulators on how to incorporate this in capital regulations and stress tests. The challenge lies in how to model the evolution of such balance sheet items. On the other hand, a static balance sheet approach lets a bank's balance sheet size be constant over the scenario horizon. A static balance sheet approach is less realistic but easy to implement and evaluate.

2.3.1 Scenario Design - Hypothetical vs. Historical

An important aspect of stress testing is the scenario design; these scenarios could be historical or hypothetical. Both methods rely on a judgment of which macro-variables to include and an assessment of the impact on the resilience of individual banks and the financial sector as a whole. When designing a historical scenario, the main idea is to rely on actual historical episodes of banking crises or historical evidence about the distribution of risk factors (Herring and Schuermann 2022). In such a design, the paths of economic and financial market variables associated with past loss events are re-run to explore the impact of a repeat occurrence (Das et al. 2022). Some popular events in history include the Asian financial crisis of 1997, the Dotcom crash of 2000 and 2002, as well as the Global Financial Crisis of 2008. The apparent danger is that history seldom repeats itself. Expert judgment is of more advanced character in the design of a hypothetical scenario. Hypothetical scenarios are based on the foundation that future economic shocks will not likely replicate past events. The paths of shock variables are chosen to be consistent with economic theory and practices. Although these scenarios may be more contested on the grounds of plausibility, such exploratory designs may be an especially useful way to deal with changes in market structure or new instruments (Herring and Schuermann 2022).

2.4 The Norwegian Banking Sector

The banking sector in Norway encompasses both commercial banks and savings banks. Allowance for accepting deposits from the general public is what sets them apart from other types of financial institutions (Finanstilsynet 2022a). Private households in Norway have an incredibly high level of debt, and both the household sector and non-financial companies have most of their debt originating from the banking sector. As a result, banks play a crucial role in the Norwegian economy. Nonetheless, the size of the Norwegian banking sector is relatively modest compared to those of other countries, mainly due to a smaller proportion of assets held with foreign counterparties (Lund and Walle 2019).

Norwegian banks obtain their financing from deposits, market-based funding, and equity. Deposits, which come from both private individuals and companies, make up 40 percent of the average Norwegian bank's total funding for lending (Norges Bank 2022a). Market-based funding primarily consists of subordinated unsecured bonds, senior unsecured bonds, and covered bonds, which together finance around 30 percent of the average bank's total lending. Senior unsecured bonds cover lending to businesses and some loans to private households, whereas covered bonds are mainly used for lending to private households and secured with residential properties. Due to this security, covered bonds are a cheaper funding source than unsecured bonds and are less sensitive to volatility in uncertain times. In addition to its usage in funding, covered bonds can also be held to meet liquidity requirements and provide security for borrowing from the Central Bank of Norway (Norges Bank 2022b).

Covered bonds are therefore in high demand by banks, both as investors and as a source of funding. However, this interconnection between banks, where a bank's financing serves as another bank's liquidity reserve, is viewed by the Central Bank of Norway as a potential threat to financial stability. In a potential economic downturn where banks may be forced to sell their covered bond holdings at substantial losses, combined with a sharp decline in residential property prices, this interconnection between banks could worsen the situation.

Lending represents the most crucial asset for Norwegian banks, as the primary source of income through interest on loans. Most of the lending is issued in Norwegian Kroner, with 50 percent of total loans to private households and 26 percent to corporations (Norges Bank 2022a). Forty-seven percent of all corporate lending consists of loans to commercial properties, which the Central Bank of Norway views as another weakness in terms of financial stability. As Norwegian banks are highly exposed to this sector, a severe decline in commercial property prices could result in significant loan losses for Norwegian banks. Historically, commercial property has been a significant source in the explanation of bank losses (Sørensen and Solheim 2014).

Losses on lending in Norway have remained at low levels for the past 30 years. After the Norwegian banking crisis at the beginning of the 1990s, which resulted in losses exceeding 4 percent of total lending at the highest, Norwegian banks were subject to stricter capital requirements than international banks (Norges Bank 2022a). Besides experiencing relatively low loan losses during the 2007-2009 financial crisis, Norwegian banks were better capitalized than foreign banks and made it relatively well through the crisis. Loan losses may challenge the solvency of one bank, and due to the close interconnection between banks and similarities of their credit exposure, problems in one bank quickly contaminate others and further destabilize the economy. A well-capitalized banking sector can help banks withstand periods with significant losses and minimize the negative impact on the economy. This forms the basis of the gradually increasing scope of banking regulation.

2.4.1 Regulations and Capital Requirements

The banking industry in Norway and globally is subject to extensive regulations that have become increasingly complex. The Basel Framework heavily influences these regulations, and specific regulations in various countries are based on it. The Basel Committee was formed by central bank Governors of ten countries in 1974 to respond to the disruptions witnessed in international currency and banking markets (BIS 2019). Initially, the Committee aimed to increase financial stability, improve global banking supervision standards, and ensure adequate and consistent supervision across member jurisdictions. Presently, 45 institutions from 28 jurisdictions are involved in the Committee.

While the Basel Committee's initial emphasis was on supervision, it soon became evident that there was a need for a common capital adequacy framework for all participating institutions. Both to enhance the stability of the international banking system and eliminate competitive inequalities arising from different national requirements. An agreement was to introduce a weighted approach to the measurement of risk. The Basel Capital Accord was released in July 1988 and established the most significant requirement, a minimum ratio of capital to risk-weighted assets (RWA), set at 8 percent (BIS 2019). Calculations of RWA and capital adequacy ratios were initially based on credit risk and expanded to include market risk during the 1990s.

In the early 2000s, the Basel framework was developed to better fit the underlying risks seen with the growingly complex nature of financial innovations. The foundation was based on three pillars, where Pillar 1 was a continuation and development of the minimum requirements introduced in the Basel Capital Accord. The second pillar comprises the supervisory review of an institution's capital adequacy and individual institutions' internal processes regarding capital adequacy. The third pillar required individual banks to publicize capital and risk exposure information to enhance market discipline. The financial crisis in 2007-2009 led to the development of Basel III, which is the current framework. An important reason why the crisis became so severe was due to the excessive risk-taking by banks and the fact that many institutions were highly leveraged, with liquidity buffers of poor quality (BIS 2019). A significant revision of the framework was needed.

In Basel III, numerous buffers on capital and liquidity were established to create a "defense line" for banks in potential future economic downturns and periods of uncertainty, besides the continuation of the three pillars from Basel II. Focus has been heightened on the quality and quantity of regulatory capital, with the common equity tier 1 (CET1) serving as the base (BIS 2019). The capital conservation buffer was introduced to safeguard the minimum capital requirement during severe future downturns. The counter-cyclical buffer was also implemented to make banks build capital in good times and hence be a source of capital to wear off in bad times. The leverage ratio was introduced as a capital solvency measurement that disregarded any risk-weighting of assets. Additionally, the concept of systematically important banks was introduced, consisting of Global Systemically Important Banks (GSIB) and Domestic Systemically Important Banks (DSIB). Banks that fall under either of these categories are subject to stricter capital requirements and reporting. All buffers on capital is a pillar 1 requirement, and must consist of CET1. In terms of liquidity, the Liquidity Coverage Ratio (LCR) was established as a requirement to make banks maintain enough liquid funds for handling a stress period of 30 days. The Net Stable Funding Ratio (NSFR) was also established to resolve potential mismatches on maturity in the balance sheet. The European Union laws for capital regulations CRR/CRD IV, which implements Basel III, are fully implemented in Norway as of December 31, 2019 (Norges Bank 2022a).

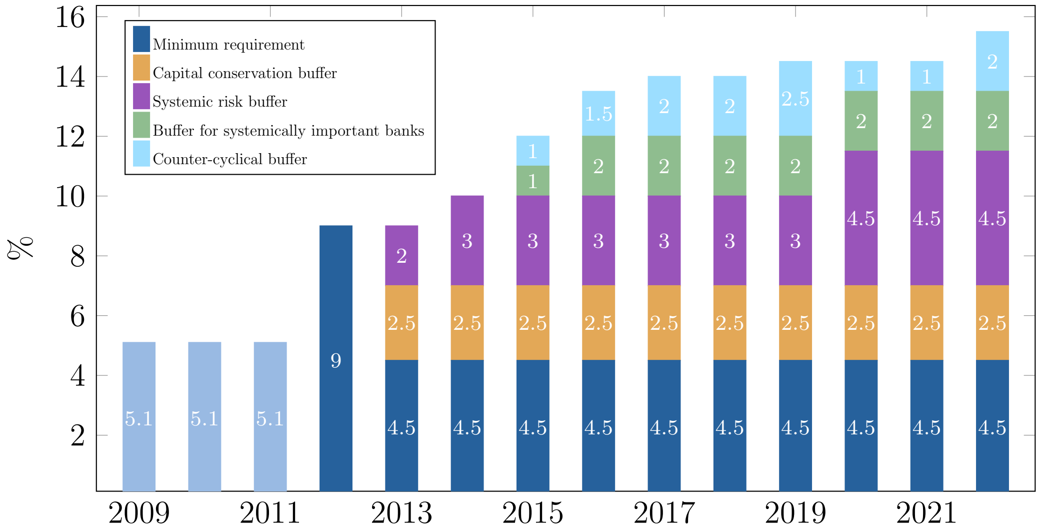


Figure 2: *Pillar 1 CET1 requirements for Norwegian banks (Andersen and Juelsrud 2022). Percent. 2009 – 2022.*

The pillars of the Basel framework play a central role in the regulation of banks by the Financial Supervisory Authority of Norway and the Central Bank of Norway under the requirements outlined in CRR/CRD IV. Since 2021, the Central Bank has been given decision-making responsibility for the countercyclical capital buffer and advisory responsibility for the systemic risk buffer (Pengepolitisk Rapport 2021). The Central Bank of Norway sets the countercyclical capital buffer requirement four times a year, and the banks have one year to adapt to the new requirement.

2.4.2 Minimimum Requirements and Buffers in Norwegian Banks

Norwegian banks must maintain a minimum CET1 ratio of 4.5 percent of RWA, with an additional requirement of 1.5 percent for Tier 1 capital, resulting in a total Tier 1 ratio of 6 percent. The minimum requirements for total capital, Tier 1 and Tier 2, are 8 percent. Banks are also required to maintain a capital conservation buffer of 2.5 percent, a counter-cyclical buffer of 1.5 percent, and a systemic risk buffer of 4.5 percent, all of which must be composed of CET1. Overall yielding a CET1 ratio requirement for Norwegian banks at 13 percent of RWA (Finanstilsynet 2022c). The DSIBs in Norway are DNB, Kommunalbanken, Nordea Eiendomskreditt, and SR Bank. DNB are required to hold additional CET1 buffers of 2 percent while the three latter are required to hold additional CET1 buffers of 1 percent. Figure 3 below shows the development of the CET1 ratio and leverage ratio for Norwegian Banks since 1996.

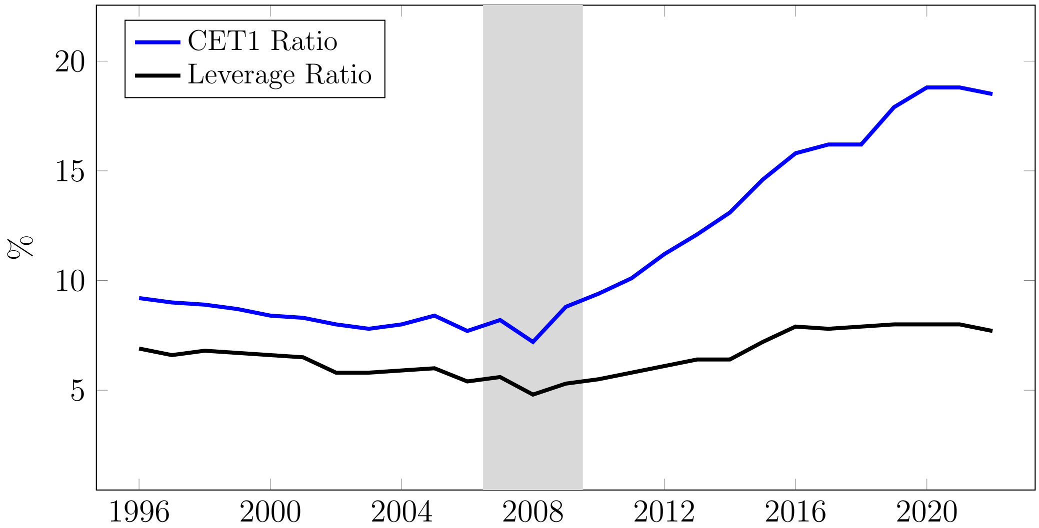


Figure 3: *The Norwegian banking sector has seen a consistent rise in capital adequacy since the 2008 global financial crisis, denoted by the gray shaded area (Norges Bank 2023). Percent. 1996 - 2022.*

2.4.3 Pillar 2 and Liquidity

Pillar 2 mandates banks to conduct internal assessments of their capital adequacy (ICAAP), which are examined by the Financial Supervisory Authority of Norway through the Supervisory Review and Evaluation Process (SREP) (Finanstilsynet 2022e). Based on these evaluations, additional capital requirements may be imposed. Stress testing is crucial in these assessments, as it helps determine the potential CET1 capital loss for banks under severe but plausible stress scenarios.

Liquidity requirements adhere to the guidelines outlined in the CRR/CRD IV. The LCR mandates that banks maintain liquid asset holdings at least equivalent to the net liquidity outflow under stressed conditions in money and capital markets over a 30-day period. The NSFR is a ratio that must always exceed 100 percent (Finanstilsynet 2022d). Stress testing is also a vital tool for evaluating banks' liquidity risk. Additionally, the central bank can supply extraordinary liquidity to individual banks and the entire system when alternative means are insufficient and financial stability is at risk. Acting as a lender of last resort, the Central Bank of Norway monitors the overall financial system, emphasizing the prevention of systemic failure.

3 Data

As mentioned earlier, most stress tests are performed by regulatory bodies or central banks, which already hold vast amounts of bank-specific or general economic data. The main body of research regarding stress testing has been conducted within the US or the EMU, where there is more data on failed entities than in the Norwegian banking sector. We focus exclusively on Norwegian banks and are limited to publicly available data. Our method for data extraction creates a framework that is transparent and makes this study easily replicable.

Our overall objective is to develop two models for a macroprudential Top-down stress test on the Norwegian banking sector. The models developed should identify the crucial macroeconomic variables that explain the development of selected profit and loss items in adverse scenarios. Our goal is to examine how large fluctuations in these variables alter the solvency of the Norwegian banking sector. To estimate the models, data on macroeconomic time series is necessary. Additionally, various banks may respond differently to macroeconomic changes. It may therefore be necessary to incorporate individual banking variables into the models to account for potential heterogeneous effects.

3.1 Data Collection

We have collected data from the Norwegian Banks Guarantee Fund's quarterly reports on Banks with operating licenses in Norway. These reports are based on raw accounting data and some key ratios and are submitted by every member of the guarantee fund. Data were available for the period of Q4 2013 up until Q4 2022, resulting in 37 quarterly observations for each bank.

Some pre-processing and cleaning of the data were necessary. Every report was structured somewhat differently in terms of economic variables and the total number of banks included. Our first step in preparing the data was to combine the quarterly reports into a main file containing panel data for every record and bank[1]. The accounting data format was structured after the Norwegian standard chart of accounts (NS4102). The variables chosen for the final data set were accounts included in all 37 different reports. This led to an initial data set consisting of 86

[1]The transformation and merging of data sets were done in the Power Query Editor function of Microsoft Excel.

financial variables and a total of 168 individual banks for a combined 534 576 observations. Further reduction of the data set was needed as it contained a lot of missing values due to mergers and newly established banks. As discussed in Section 2, earlier stress tests performed by the central bank of Norway only include a fraction of the total banks in Norway to evaluate the combined sector performance. We employ a similar method and restrict our analysis to eight of Norway's ten biggest banks by total assets. This is done due to ease of computation and the fact that these banks cover about 60% of the total deposits from customers in the Norwegian banking sector. Table 1 presents the banks we decided to include in our analysis. Note that Sparebank 1 Østlandet is a result of a merger between Sparebanken Hedmark and Bank1 Oslo Akershus AS. We handled mergers the same way as the Norwegian Banks Guarantee Fund does in their reports by summing the accounting figures and retaining the acquiring bank's capital adequacy and liquidity figures.

Bank	**Total Assets**	**Share of Total Deposits**	**Geographical Location**
DNB Bank ASA	1 235 125	38,1 %	All of Norway
SpareBank 1 SR-Bank ASA	138 043	4,3 %	Southern Norway
SpareBank 1 SMN	112 028	3,5 %	Central Norway
SpareBank 1 Østlandet	92 246	2,8 %	Eastern Norway
Sparebanken Vest	90 864	2,8 %	Western Norway
SpareBank 1 Nord-Norge	76 209	2,4 %	Northern Norway
Sparebanken Sør	63 185	1,9 %	Southern Norway
Sparebanken Møre	58 179	1,29 %	Northwestern Norway

Table 1: *Overview of Banks included in our analysis. Total Assets reported in NOK 000 000's. Source of figures: Finans Norge 2023.*

We argue that, by incorporating these banking institutions, we are able to capture a substantial proportion of the market share in our analysis. The location of these banks provides us with a geographical coverage that encapsulates the majority of Norway. The dimensions and geographical distribution of these banks play a critical role in mitigating idiosyncratic risk while preserving the systemic risk under evaluation. Consequently, this has led to the formulation of a balanced panel data set, encompassing eight banks with 37 quarterly observations each.

3.2 Bank Specific Variables

The variables utilized for each financial institution encompass a range of economic data, including information from income statements, balance sheet statements, loss provisions, commitments in default, and capital adequacy ratios, among other key indicators. In addition to these quantitative variables, the reports from the Norwegian Banks Guarantee Fund also present qualitative information about newly established banks and any recent mergers that have taken place within the banking sector. Some variables featured in the income statement were reported as Year-to-Date (YTD) values. To address this, we transformed the YTD values to a format that better suited our analysis. For a comprehensive list of all the variables included in our study, please refer to Table 3 in Appendix A.

3.3 Macroeconomic Variables

To determine which macroeconomic variables to include in the data set, we referred to the stress test outlined in the Norwegian Central Bank's 2015 report on financial stability. Our final macro data set consists of 9 domestic variables with quarterly observations from the last quarter of 2012, and we make use of up to 4 lags. The variables included are the 3-month NIBOR short-term interest rate, 10-year Norwegian government bond yields, consumer price index, GDP, unemployment rate, credit indicator K2, Brent spot, housing prices, and the Oslo Stock Exchange Benchmark Index. The macroeconomic variables are described in more detail below:

1. **The 3-month Norwegian Inter-Bank Offered Rate** (NIBOR) is the short-term interest rate in the Norwegian money market. It is decisive for the financing cost of Norwegian banks, making it an important factor in determining customer interest rates. We obtained the rate from the FRED database with the ticker *IR3TIB01NOM156N*.

2. **10-year Norwegian Government bond yields** (10YR) is used to measure long-term interest rates and indicate investors' beliefs about the future. The rate is obtained from the FRED with ticker *IRLTLT01NOM156N*.

3. **The consumer price index** (CPI) tracks changes in the prices of goods and services consumed by private households in Norway and is often used as a measurement for inflation (Statistics Norway 2023c). We collected monthly

data from Statistics Norway (SSB) and calculated quarterly means for inclusion in our data set.

4. **The Real Gross Domestic Product** (GDP) represents the total economic activity in Norway. It is an expression of the economic added value earned through the production of goods and services during a specific period (Statistics Norway 2023b). The data is obtained from the FRED database with the ticker *CLVMNACSCAB1GQNO*.

5. **The registered unemployment rate** (UR) in Norway measures the percentage of the workforce currently without work (Statistics Norway 2023a). The workforce is everyone who offers their labor on the labor market. The data is obtained from SSB.

6. **The credit indicator** (K2) tracks the growth of domestic debt in Norway, held by various agents in the economy (Statistics Norway 2023d). The growth of total debt in the economy is important for determining the banks' interest income and the evolution of their portfolio of problem loans. Data is obtained from SSB.

7. **The Brent spot** (OIL) is the price of a barrel of North Sea oil measured in US dollars and is often viewed as a significant factor explaining development in different Norwegian economic measurements. Daily data is obtained from the FRED database and aggregated to quarterly mean under the ticker *DCOILBRENTEU*.

8. **The development of housing prices** (HP) is captured with the growth in the value of used housing prices in Norway. Housing prices can be an indicator of how robust the private household economy is; a severe fall in prices may reduce the wealth of private households and further affect banks' holding of problem loans. Data is obtained from SSB.

9. **The Oslo Stock Exchange Benchmark Index** (OSEBX) is included as an indicator of how well the markets are performing. We collected daily data and aggregated it to quarterly mean. Data is obtained from Yahoo Finance.

4 Methodology

To better understand the dynamics in our model, we will provide insight into techniques used and explain variables that are considered important. We start by explaining our approaches for estimating the models before we present the adverse scenario used in the stress test and projections of the macroeconomic variables. Finally, we present the methodology for projecting and modeling the profit and loss (P&L) statements and selected balance sheet items for the individual banks. As mentioned in section 2, our work takes inspiration from models developed by the Norwegian Central Bank. However, due to the limited availability of qualitative information, our scenarios are comparatively simpler.

4.1 Fixed Effects

The standard approach for estimating panel data using pooled Ordinary Least Squares (POLS), is a simple estimation method and can have some unfavorable effects. The pooled OLS approach may lead to biased and inconsistent estimates due to unobserved heterogeneity (Wooldridge 2020). To address this issue, we used a fixed effects model, which accounts for the unobserved heterogeneity across entities in the panel data. By allowing each entity (Bank) to have its own intercept, the model accounts for unobserved factors that are different across entities but constant over time. Consider the Standard POLS model for the estimation of a panel dataset:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \tag{1}$$

Using a fixed effects model, we allow the disturbance term to be split, where $u_{it} = \mu_i + \upsilon_{it}$. This decomposed disturbance term represents both the individual specific effect μ_i, and the "remainder disturbance" that varies over time and entities, υ_{it}.

Given the strong assumption that individual-specific time-varying covariates have to be uncorrelated with the time-constant error term, any estimation of β is likely inconsistent and biased. To resolve this, we apply the fixed effects model by including dummy variables, termed the least squares dummy variable approach (LSDV):

$$y_{it} = \beta x_{it} + \mu_1 D1_i + \mu_2 D2_i + \mu_3 D3_i + \cdots + \mu_N DN_i + \upsilon_{it} \tag{2}$$

Here, $D1_i,\ D2_i,\ D3_i, \ldots,\ DN_i$ represents dummy variables for each entity. Where the dummy takes the value 1 for all observations of a specific entity and zero otherwise. To avoid the "dummy variable trap", we create $N-1$ dummies, such that the first variable takes the value zero. By introducing entity-specific dummy variables in equation (2), we are able to relax the exogeneity assumption that is required when running POLS regression for consistent estimation. The main benefit of fixed effects estimations is that the potential sources of biases in the estimations are limited in comparison to classical OLS models (Collischon and Eberl 2020). For an OLS model, any correlation between unobserved variables and the outcome or treatment variables results in a biased estimate of the treatment effect. In contrast, FE models limit the sources of bias to time-varying variables that correlate with the treatment as well as with the outcome over time (Collischon and Eberl 2020). Regarding FE estimation, they usually give more credible results than OLS when analyzing panel data, however, there are some shortcomings to this method as well[2].

4.2 Variable Selection

Suppose we have an individual bank response variable Y, and $X_1, \ldots, X_p$ is a set of potential explanatory variables as vectors of n observations, consisting of different macroeconomic variables and their lags, potential transformations, and individual bank variables. Developing models for macroeconomic Top-down stress tests involves selecting the right set of these explanatory variables. Many macroeconomic variables may affect each other in complex ways, and when including many lags or transformations, we get a large number of predictor variables to choose among. When having p possible variables to include in the model, we get a potential 2^p models to evaluate. With an increasing number of p, computational costs are getting exponential for a naive algorithm. There exist different approaches for solving the variable selection problem. We consider a stepwise regression variant, and a regularization method.

4.2.1 Stepwise Regression

Stepwise Regressions consist of Forward Stepwise Regression and Backward Stepwise Regression. Forward Stepwise Regression starts with an empty model, adding one variable at a time based on the variables' impact on model fit, for example, measured

[2] See Wooldridge 2020 for a detailed explanation of limitations.

by the highest R^2. Backward Stepwise Regression starts with a model including all possible explanatory variables, and for each step, a new model is created with one less variable than in the previous. This process continues until there is only one variable left. Variables that are removed from each step is the one that contributes the least to model fit (Chan-Lau 2017). Both methods create a set of p models to evaluate, where each model consists of k variables, for $k = 1, \dots, p$. Based on this set of models, the "best" and chosen model are based on an optimization criterion, for example, the model with the lowest Akaike Information Criterion (AIC)[3]. Computational costs for Stepwise Regression are substantially lower than a naive algorithm; $1 + p(p+1)/2$. We use the Forward Stepwise technique to estimate our stepwise regression models.

4.2.2 Regularization Methods

Least square estimates, as obtained from a stepwise regression, tend to prioritize lower bias at the expense of higher variance, which can potentially negatively affect the model's prediction accuracy. The problem of balancing bias against variance is known as the bias-variance tradeoff. A bias too high will not be able to capture the complex, underlying relationships in data, resulting in underfitting. However, in seeking to minimize bias, one risks fitting the model to the noise in the data. Especially when we have a large set of predictor variables, adding more variables to the model decreases the bias. However, it also increases the variance of the estimated coefficient, which may cause overfitting. An overfitted model performs poorly out-of-sample. The bias-variance sweet spot is where the model is complex enough to capture the underlying patterns in the data but avoids fitting the noise. An approach to deal with this issue is to use a regularization method. Regularization methods penalize complex models and therefore reduce the chances of overfitting. All non-zero coefficients take on a penalty; the penalty term reduces the value of the coefficients. A general penalty used in different regularization methods is on the form $(\sum_{j=1}^{p} \beta_j^q)^{1/q}$. We use the Least Absolute Shrinkage and Selection Operator (the Lasso) introduced by R. Tibshirani in 1996.

[3] A formula-based model is selected by AIC, through the step function in the package: stats (version 3.6.2) in R.

4.2.3 The Lasso

Given a linear regression with standardized predictors x_{ij} and centered response values y_i for $i = 1, 2 \ldots, N$ and $j = 1, 2, \ldots, p$, the Lasso solves the penalized regression problem of finding $\beta = \{\beta_j\}$ to minimize:

$$\sum_{i=1}^{N}(Y_i - \sum_j x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{3}$$

Considering the general penalty term mentioned in the above section, the Lasso uses $q = 1$ and is thus a regularization method that uses the l_1 norm penalty. By the properties of the l_1-penalty, the Lasso can both shrink coefficients and set unimportant ones to zero. Subset selection increases as q approaches zero; the Lasso uses the smallest value of q that still yields a convex problem (Tibshirani 2011). A convex problem is computationally feasible. Furthermore, Lassos' ability to both remove variables from the set of final explanatory variables and shrink coefficients makes it an appealing method for developing sparse models. Leaving variables out from the final set of predictors is also a convenient way to resolve the problem when variables have a high level of multicollinearity, which can be the case for macroeconomic variables (Chan et al. 2022).

λ in equation (3) is the parameter that balances bias against variance; an optimal parameter value can be calculated with cross-validation (Chan-Lau 2017). The procedure selects the estimator's minimum estimated test error rate, calculated from a subset of the training set used in estimating the model. Considering K-fold cross-validation, it randomly divides the training set into K different subsets. One of these is kept as a validation set, while the remaining $K - 1$, estimates a model and gives a range of λ values. This process is repeated using all K subsets as validation sets, yielding K estimates of the test error rate. The K-fold estimate is the average over these K estimates. The best parameter is the one with the lowest K-fold estimate, λ_{min}. We use 10-fold cross-validation in training our Lasso model[4].

4.3 Stationarity

When working with time series, it is a requirement that the data is stationary. Regressions on non-stationary data will have some unwanted behavior and properties;

[4]For Lasso estimation we use the package: glmnet (version 4.1-7), in R.

we may end up with spurious regressions, and asymptotic analysis will no longer be valid (Brooks 2019). For the sake of this paper, we consider weak stationarity, which is defined as a series with constant mean, constant variance, and constant autocovariance:

$$E(y_t) = \mu \tag{4}$$

$$E(y_t - \mu)(y_t - \mu) = \sigma^2 < \infty \tag{5}$$

$$E(y_{t1} - \mu)(y_{t2} - \mu) = \gamma_{t2-t1} \ \ \forall \ \ t1, t2 \tag{6}$$

The macroeconomic variables in our dataset that are considered non-stationary is CPI, GDP, K2, HP, OIL, and OSEBX. There are several ways to transform non-stationary series to stationary; we log-transform the non-stationary variables and then differentiate them once. NIBOR, 10YR, and UR are considered stationary in their original form. The banking variables that share the same time trend, like income elements and balance sheet items, are normalized by dividing the income values by total assets or total loans.

4.4 Scenario Design and Macroeconomic Variables

The main goal of a Top-down stress test is to evaluate how banks perform in a severe macroeconomic stress scenario. The process of designing such scenarios involves a degree of discretion. Although it is a hypothetical exercise, the scenarios should reflect an outcome that could occur, even though with a minuscule probability. We mainly project our macroeconomic variables with magnitudes observed in historical data. The financial crisis in 2008 is a recent example of a crisis that had a significant impact on the banking sector internationally, even though it was alleviated in the Norwegian banking sector by emergency measures from the Central Bank of Norway. The Norwegian economy did also face different consequences than the Euro Area and the United States. In the projections of the macroeconomic variables, we use some data from the financial crisis both from Norway, the US, and the Eurozone, some data from the Norwegian banking crisis in the early 1990s, and some numbers from the stress test in the Central Bank of Norway's 2022 Financial Stability Report. The scenario design is thus mostly historical. A weakness of this approach is as mentioned earlier, that future crises may look different from previous ones. Undiscovered macroeconomic connections may materialize and affect banks in an entirely new way. We project the variables 12 quarters ahead after Q4 2022.

We project NIBOR based on the observed growth over the 12 quarters from Q1 2008 and onward. We assume that uncertainty in the money market initially leads to an increase in risk premia for short-term yields that drives the rate up, which then decreases after the Central Bank of Norway's policy rates take effect. 10YR follow the same growth as the 10-year Norwegian government bond yields did in the 12 quarters after Q1 2008. CPI develops similarly to growth in Norway's consumer prices from Q1 2008 and onward. The GDP growth rate mirrors the growth rate in the Euro Area GDP from Q1 2008 and the following 12 quarters. Over the projected three-year period, GDP is projected to grow at annual rates of -2.66 percent, -0.8 percent, and 1.99 percent, respectively.

The unemployment rate in Norway did not increase as much as it did in the Euro area during the financial crisis. Therefore, we looked back at the unemployment rate in Norway between 1991 and 1994 after the banking crisis to find values that fit a Norwegian context. UR in our scenario stays around 6 percent over a three-year period. For K2, we used the same growth rate as the stress test in the Central Bank of Norway's Financial Stability Report for 2022, which considers both K2 towards private households and non-financial firms. We estimate our models on total outstanding credit (K2 public). Approximately 70 percent of K2 public consists of loans to private households, while non-financial firms account for approximately 30 percent. We aggregated this information to obtain the growth rate for K2 in our scenario. Over the three years, growth rates for K2 are projected to be -1.7 percent, -0.86 percent, and 1.43 percent, respectively.

We project OIL with the same growth rate as that observed for the Brent spot price from Q1 2008 and the following 12 quarters. Regarding HP, the years before the banking crisis in Norway in the 1990s yielded a significant decline in housing prices. Since we could not find data for this period, we we use the same evolution as the property prices in the US during the subsequent 12 quarters after Q1 2008 for projecting HP. The data from the US yields a development of housing prices over the three projected years of -13.84 percent, 1.25 percent, and 4.51 percent, respectively. A reduction of -13.84 percent is severe; however, it is less than the -22 percent scenario for the worst year used in the stress test in the Central Bank of Norway's Financial Stability Report in 2022. To project OSEBX, we look at the development of the NASDAQ composite index in the 12 consecutive quarters after Q1 2008. Based on this growth, OSEBX is in the stress scenario projected to decrease by 31 percent in the first year before it increases by 45 percent and 11 percent in the two following years. Quarterly development of the projected macroeconomic variables can be found in table 2 below.

Period	2022	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
3 Month NIBOR	3,37	3,53	3,69	4,12	4,33	3,64	1,18	0,96	0,76	1,18	1,38	1,58	1,78
10 year government bonds	3,27	2,89	3,18	3,20	2,53	2,24	2,58	2,62	2,52	2,43	2,05	1,74	1,87
Housing prices	-0,3	-6,64	-5,63	-2,22	-2,45	-1,11	-0,27	0,14	-0,40	-1,20	-1,93	-1,26	-2,16
CPI Growth	1,04	1,00	0,27	1,30	0,94	-0,07	0,93	0,00	0,56	1,44	0,58	-0,72	0,98
GDP Growth	0,19	0,51	-0,34	-0,52	-1,83	-3,10	-0,02	0,41	0,42	0,44	0,97	0,42	0,59
Unemployment rate	1,71	5,70	5,30	6,20	5,90	6,00	5,40	6,40	6,10	6,20	5,10	5,80	5,80
K2 growth	1,3	-0,43	-0,43	-0,43	-0,44	-0,21	-0,22	-0,22	-0,22	0,36	0,36	0,36	0,35
Brent OIL*	88,72	97,11	121,62	114,60	54,76	44,51	58,80	68,32	74,76	76,39	78,65	76,96	86,62
OSEBX*	1189,00	1033,50	1072,59	1013,11	708,40	657,25	765,48	876,06	957,32	1007,73	1035,46	988,37	1122,35

Table 2: *Quarterly change in macroeconomic key variables used in stress scenario through 3 years. 2022 is the real Q4 observation in Norway and the starting point for our scenario. The change is measured in percent and * marks variables measured in monetary value, Brent in USD, and OSEBX in NOK, respectively.*

4.5 Projections of Bank Specific Variables

In a severe stress scenario, deficits are the main driver of the depletion of banks' capital. Our focus for projecting banks' performance lies primarily in their income statements. We divide the banks' income statements into different components, including net interest income, net commission income, dividends from equity interests, changes in the value of financial instruments, personnel costs, other operating expenses, losses on loans, and taxes. Some components are projected using developed models, while others rely on simple rules. The selected balance sheet items either follows the outcome from the income statements, or projected with simple rules.

4.5.1 Net Interest Income

Net interest income is the most significant contributor to a bank's earnings and is calculated as the difference between interest income and interest costs. Development in NIBOR plays a crucial role in determining the interest rate at which banks can borrow in the money market, thus affecting both interest income and interest costs.

Outstanding loans and lending growth are decisive for a bank's total interest income. Predicting the development of a bank's lending portfolio in a severe stress scenario is challenging. Different banks have varying lending-to-assets ratios, and lending growth rates may, in reality, differ across entities. However, we assume that all banks' lending growth follows the credit growth in the economy. Typically, a cooling down of the economy tends to reduce the general credit growth, further impacting individual banks' lending.

Interest on deposits and market financing are primary drivers of interest costs. The cost of market financing is especially closely connected to NIBOR. Total interest costs on deposits are dependent on the bank's deposits-to-assets ratio. For simplicity, we assume that the deposits-to-assets ratio is constant through the stress scenario, equal to the average ratio through 2022. In reality, a possible banking crisis may lead to a bank run, which would severely reduce the deposits-to-assets ratio. We ignore this scenario because of no previous bank runs in Norwegian banking data. This is probably due to the fact that more than half of deposits in Norwegian banks are guaranteed. We model net interest income with a Forward Stepwise and Lasso fixed effects regression. The basis of estimation is net interest income in the income statements, divided by total assets. Independent variables are the present and one-period lagged values of the lending-to-assets ratio, present and one-period lagged values of the deposits-to-assets ratio, and the macroeconomic variables. Projections of the variable are dependent on the growth in lending-to-assets, deposits-to-assets, and the macroeconomic variables.

4.5.2 Other Income and Expenses

Other income and expenses include net commission income, dividends from equity, personnel costs, other operating expenses, and taxes. These variables should be less cyclical and are therefore chosen to be projected with simple rules. The banking model described in the Central Bank of Norway's 2015 Financial Stability Report shows that net commission income remains constant throughout the stress period, equivalent to the average of the previous four quarters before the scenario's start. We apply this approach for all the other income and expenses except taxes. We calculate the different components' average size in relation to total assets over 2022 and use this as a constant throughout the stress period. Obviously, this is a simplification. For instance, banks may reduce personnel costs or other operating costs to withstand periods of deficits. Taxes on profits is set to 22 percent; in periods of deficits, the banks obtain a deferred tax benefit.

4.5.3 Change of Value On Financial Instruments

In our data set, the individual banks hold a portfolio of various financial instruments, including bonds, certificates, equity, and derivatives. Large deviations in the value of financial instruments affect banks' capital. Shocks to the yield curve can impact the value of bonds and certificates, and a significant decline in market prices for equity can affect the value of equity holdings, as examples. As we lack a detailed breakdown of the different banks' portfolios of financial instruments, the basis of estimation is the corresponding income statement element divided by total assets. The model is estimated with a Forward Stepwise and Lasso fixed effects regression. Independent variables are the set of macroeconomic variables. Further projections of the variable depend on the evolvement of macroeconomic variables in the stress scenario.

4.5.4 Credit Losses

During historical banking crises, loan losses are the main driver of bank capital reductions. A stress test's outcome often depends on the magnitude of losses different banks suffer in the given scenario. Modeling credit losses is a difficult task. Firstly, there are limited historical observations of periods with significant loan losses, particularly when considering Norwegian bank data. The banking crisis of the early 1990s led to annual loan losses of over 4 percent of total lending. However, in our data from the end of 2013, loan losses are at very low levels. A few banks suffered some losses in relation to the 2014-2015 oil price drop; besides this, the only period of observed losses was in the first quarter of 2020 during the Covid-19 pandemic. Some banks reported annualized loan loss rates of up to 1 percent of total lending during Q1 2020. A credit loss model based on this data may not capture how losses develop following adverse shocks to important macroeconomic variables in a stressed scenario. Another aspect to consider is the technical element of banks' credit losses.

Banks are required to set aside capital for expected credit losses (ECL), known as loss provisions. After the implementation of IFRS 9, loans are divided into three stages based on their underlying probability of default (PD). For loans in stage 1 with the lowest PD, ECL, and loss provisions are calculated over a period of 12 months. Should the PD for a loan experience a significant increase, or if the engagement defaults, the loan is moved to either stage 2 or 3. In these two stages, ECL is calculated over the whole lifetime of the instrument. All the banks in our dataset, except Sparebanken Sør, calculate ECL using IRB. ECL with IRB is calculated as a product of the PD, loss-given default (LGD), and exposure at default (EAD) and can be measured at the individual customer level. Based on which approach they use, a bank can either estimate PD if they use basic IRB or a combination of PD, LGD, and EAD if they use advanced IRB, respectively (Finanstilsynet 2022b). This means that significant changes in macro-variables, such as the sharp but short-lived increase in unemployment at the beginning of the Covid-19 pandemic, may have impacted the bank's individual models, resulting in greater loss provisions. These loss provisions may not necessarily stem from actual losses but rather from "model losses".

Additionally, it is worth mentioning that some banks made adjustments outside the IRB models based on discretion, which led to higher provisions in the actual quarter (Skrede et al. 2022). The loss provisions observed in the first quarter of 2020 were not mainly due to defaulting customers; but rather a consequence of an overall rise in underlying credit risk due to higher unemployment rates, reduced GDP, and other similar factors. The increase in new loss provisions propagates into the loan loss costs reported in the income statements.

Despite these weaknesses, when trying to model credit losses on our data, we estimate a Forward Stepwise fixed effects regression and a Lasso fixed effects regression for losses. We do not have data for the different banks PD, LGD, and EAD, the dependent variable used is thus the reported credit loss in the income statements, divided by total assets. Independent variables are the set of macroeconomic variables. The resulting model provides projections of credit losses conditional on the macroeconomic stress scenario.

4.5.5 Total Assets, CET1, RWA, and CET1 Ratios

We project total assets, CET1, RWA, and CET1 ratios with fairly simple rules. Considering total assets, we assume it increases with the predicted profits over the stress horizon. Compared to reality, this is a very simple approach. There are many things banks can do in order to change their capital structure; however, more detailed projections of total assets rapidly become complex.

Usually, banks pay out dividends each year. For simplicity, we assume that none of the banks pay dividends during the stress scenario. Further, assuming that total assets are compounded with profits after tax, the CET1 will increase by the compounded amount on total assets. In periods of deficits, the deferred tax benefits are not calculated into the CET1, according to regulatory rules. Projecting CET1 ratios involves a projection of RWA, which in reality involves technical calculations on credit, counterparty, market, and operational risks. Based on our data, we do not consider detailed calculations of RWA's. We assume it increases with the same amount compounded on total assets, which is the same approach as the Central Bank of Norway's stress test in 2008 (Andersen and Berge 2008). Compared to reality, during a stress scenario where losses increase, it is convenient to think that credit risks increase. As credit risk constitutes the major part of a bank's RWA, greater credit risk would lead to higher RWA, and possibly with a greater increase than what we project in our scenarios. Summarized for the balance sheet items, our approach is a very simplified dynamic balance sheet approach, where total assets and total lending are allowed to vary over the horizon.

5 Results

In this section, we present results derived from our models on the available data, focusing on the financial performance of the banks included in our study. As emphasized in Section 2, the impact of credit losses on a bank's capital is of particular significance. Therefore, we will provide a comprehensive examination of this aspect as well.

5.1 Forward Stepwise Regression

With the Forward Stepwise Regression approach, five banks in the panel experience two periods of deficits during the stress horizon, namely DNB, SpareBank 1 SR-Bank, SpareBank 1 SMN, SpareBank 1 Østlandet, and Sparebanken Møre. Table 10 shown in Appendix D provides the predicted yearly credit losses as a percentage of total lending for the Forward Stepwise Regression. In year 2, we see a peek for all banks, with DNB obtaining the highest loss rate at 1.9 percent. The Forward Stepwise Regression for financial instruments does also predict a significant decrease in the value of financial instruments. The estimated decline in value for the various banks is approximately between 5 and 7 percent over the first two projected years.

According to the Financial Stability Report of the central bank of Norway in 2015, the outlined stress tests reveal a great initial decline in the value of financial instruments during the first quarter of the stress scenario. The decline includes a 5 percent reduction in the value of certificates and bonds, and a 30 percent reduction in the value of equities. After the first quarter, the value of financial instruments remains at the level it had in the previous year before the stress scenario. The stress test in the 2014 Financial Stability Report does in contrast show a comparatively lower initial decrease in the value of financial instruments compared to the 2015 report, however the value was set to zero for the remaining years of the stress scenario (Syversten et al. 2015).

The two stress tests mentioned employed an initial decline in the value of financial instruments, followed by a quick recovery, because of the experience from the financial crisis, where Norwegian banks income on financial instruments rapidly returned to normal levels after a decrease in the beginning of the crisis. In our stress test, a 5 percent reduction in the value of certificates and bonds, and a 30 percent reduction in equity value over the first quarter, would result in an approximate 5 percent decrease in the value of financial instruments for the banks analyzed. While the Forward Stepwise Regression predicts a larger overall decrease, the initial shock is relatively smaller. However, given the figures used in the stress tests conducted by the central bank of Norway, the predicted magnitudes are not entirely unreasonable.

Based on the projected income statements in figure 4, DNB is projected to obtain the worst result, with a predicted reduction of approximately 2 percent in its CET1 over Q4 and Q5. Based on projections of RWA, DNB's CET1 ratio are projected to decrease by 0.3 percent over Q4 and Q5.

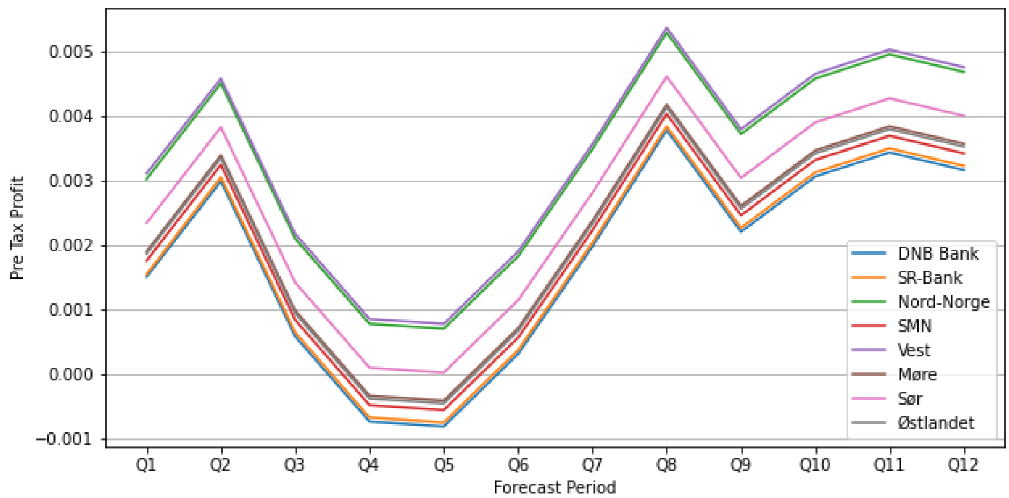
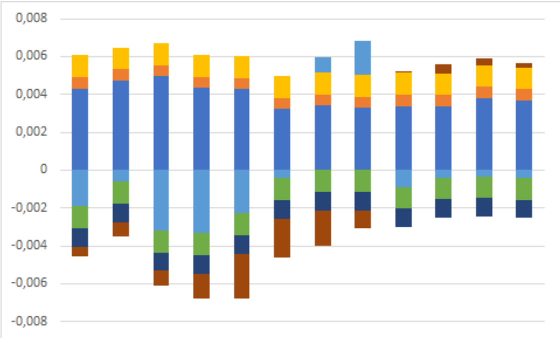
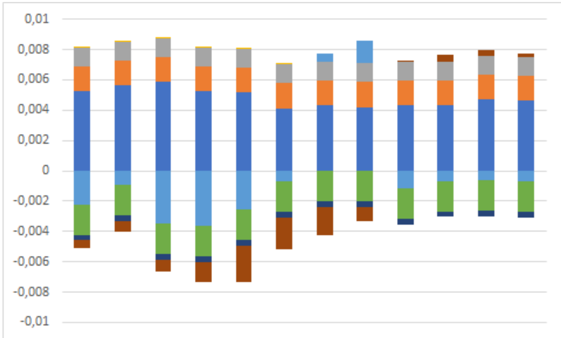


Figure 4: *Development of pre-tax profit in stress scenario with Forward Stepwise Regression.*

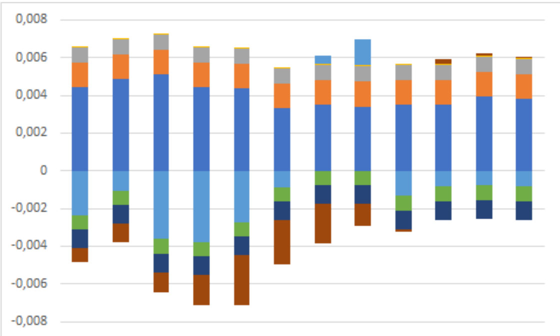
At the parent-bank level, DNB has a CET1 ratio of 21.09 percent as of 31.12.2022. DNB's overall regulatory capital requirement is a CET1 ratio of 16,9 percent, meaning that even though CET1 should fall by 2 percent, further reducing the CET1 ratio by 0.3 percent, DNB is far from using some of its buffers on capital through the scenario. Concerning CET1 for the other banks facing deficits, SpareBank 1 SR-Bank is projected to lose 1.75 percent, SpareBank 1 SMN projected to lose 1.28 percent, Sparebanken Møre projected to lose 0.7 percent, and Sparebanken Østlandet projected to lose 0.8 percent. For SpareBank 1 SR-Bank having an overall regulatory requirement of CET1 ratio at 16.85 percent and 17.89 percent CET1 ratio as of 31.12.2022, it is the bank that are closest to its capital requirements of the banks in the data set. Due to profits in the first three quarters of the scenario, SpareBank 1 SR-Bank increases it CET1 with so much, that even after the decrease in CET1 during Q4 and Q5, the CET1 ratio is above 18 percent after Q5. However, if we had applied a more detailed projection of RWA, it could have potentially accounted for the impact of higher credit risk during the initial quarters. This could have led to a more significant increase in RWA relative to CET1, resulting in a more substantial reduction in the CET1 ratio. None of the other banks are near breaching their requirements in the stress scenario. The low predicted decrease in capital for the banks might be due to the stress scenario not being tough enough. However, only 4 out of the 288 quarterly observations of income statements in the data set resulted in deficits (SpareBank 1 SR-Bank in Q1 2020, SpareBank 1 Nord-Norge in Q4 2014 and Q4 2015, and Sparebanken Vest in Q3 2014). Predicting five banks to end up with two quarters of deficits over the three projected years, with only SR-Bank having observed deficits in the data set, indicates that the scenario is stressful. Deficits among Norwegian banks happen rarely, and when it does, the banks are well-capitalized, making them sustain the deficits well. A scenario worse than ours must occur should there be a crisis in the Norwegian banking sector.



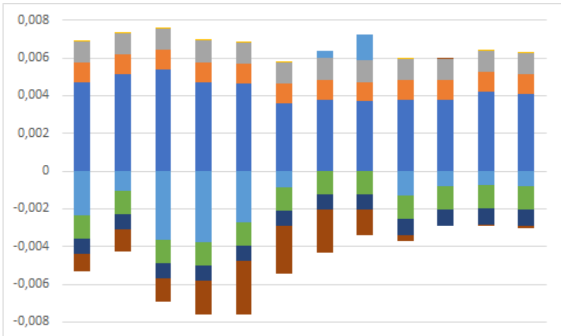
(a) *DNB Bank ASA*



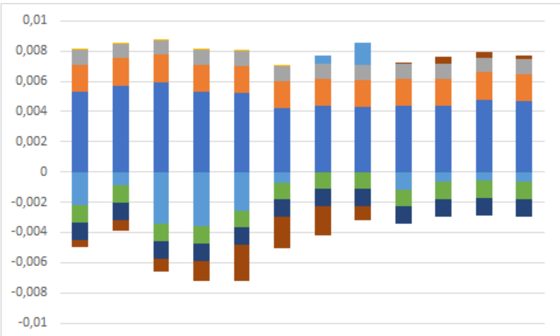
(b) *SpareBank 1 Nord-Norge*



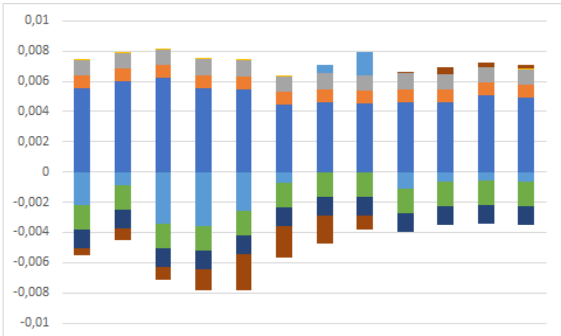
(c) *SpareBank 1 SMN*



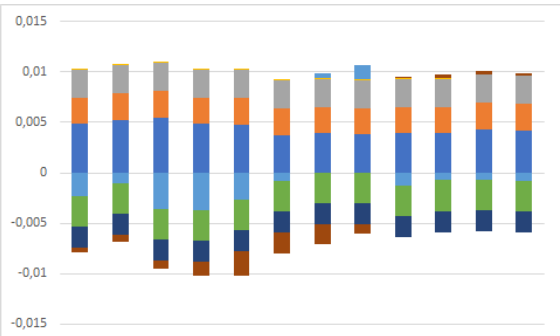
(d) *SpareBank 1 SR-Bank ASA*



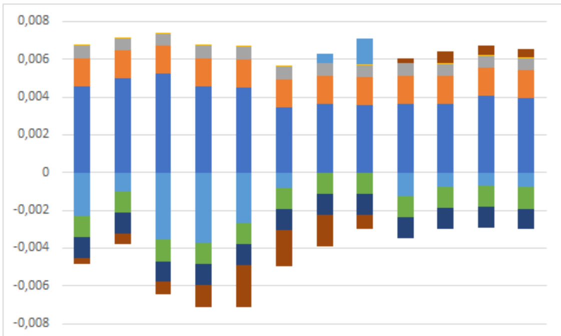
(e) *Sparebanken Vest*



(f) *Sparebanken Møre*



(g) *Sparebanken Sør*



(h) *SpareBank 1 Østlandet*

Net Interest Income | Net commission income | Dividens etc. | Other Operating Income

Change in Value of Financial Instuments | Administrative Expenses | Other Operating Expenses | Credit Losses

Figure 5: *Development of selected figures in the income statement for each bank included in our analysis by FSR. As pointed out in section 4, none of the banks pay dividends over the stress scenario, "Dividends ect" here refers to dividend income.*

5.2 Lasso Regression Model

The Lasso model estimates no periods of deficits for the eight individual banks in our data set. However, the model predicts an increase in losses over the first projected year, reaching a peak in Q5. Table 11 shown in Appendix D provides the predicted yearly loan losses as a percentage of total lending for the Lasso Regression. The Lasso predicts larger credit losses than the Forward Stepwise regression in the first year, and almost identical predictions the second year, with DNB obtaining the largest credit loss of 1.9 percent of total lending. Furthermore, the Lasso model predicts a fall in net interest income, starting from Q2.

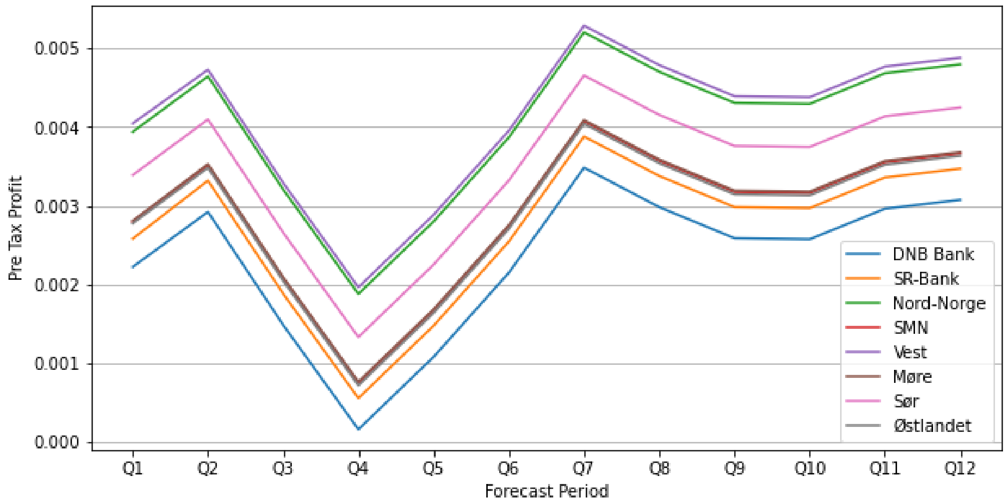
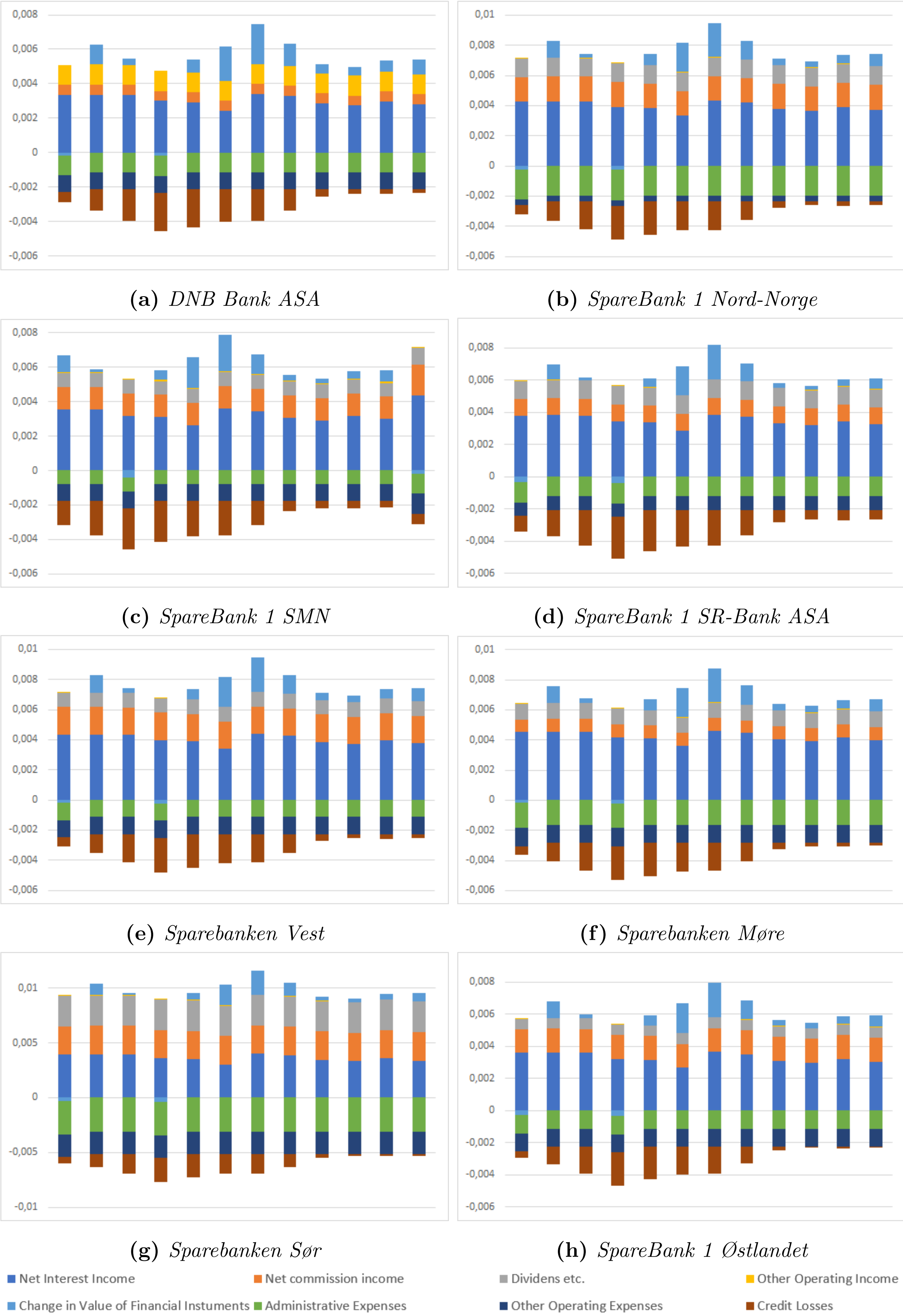


Figure 6: *Development of pre-tax profit in stress scenario by Lasso Regression.*

Looking at figure 6, we see that this combination of factors results in the lowest outcome in Q4. DNB is expected to obtain the lowest result, close to zero. When comparing the stepwise regression and the Lasso Regression, it becomes apparent that credit losses are not the primary factor leading to different predictions for the income statements over the stress horizon. The outcomes differ mostly due to changes in value of financial instruments. With the Lasso model, financial instruments do not contribute notably to the cost side throughout the stress horizon. In fact, the post tends to contribute positively to income in most quarters. It is clear that this variable can also influence the capital adequacy ratio.



(a) *DNB Bank ASA*

(b) *SpareBank 1 Nord-Norge*

(c) *SpareBank 1 SMN*

(d) *SpareBank 1 SR-Bank ASA*

(e) *Sparebanken Vest*

(f) *Sparebanken Møre*

(g) *Sparebanken Sør*

(h) *SpareBank 1 Østlandet*

Figure 7: *Development of selected figures in the income statement for each bank included in our analysis by Lasso Regression. As pointed out in section 4, none of the banks pay dividends over the stress scenario, "Dividends ect" here refers to dividend income.*

5.3 Credit Losses and Sensitivity

From Figure 8, we see that both the Forward Stepwise model and the Lasso model forecast fairly equal movements for the credit losses over the stress horizon. Both models predict the peak in Q5. The forward stepwise model predicts negative loan losses for most banks from Q9 onwards, which can be explained as a reversal of previous loss provisions.

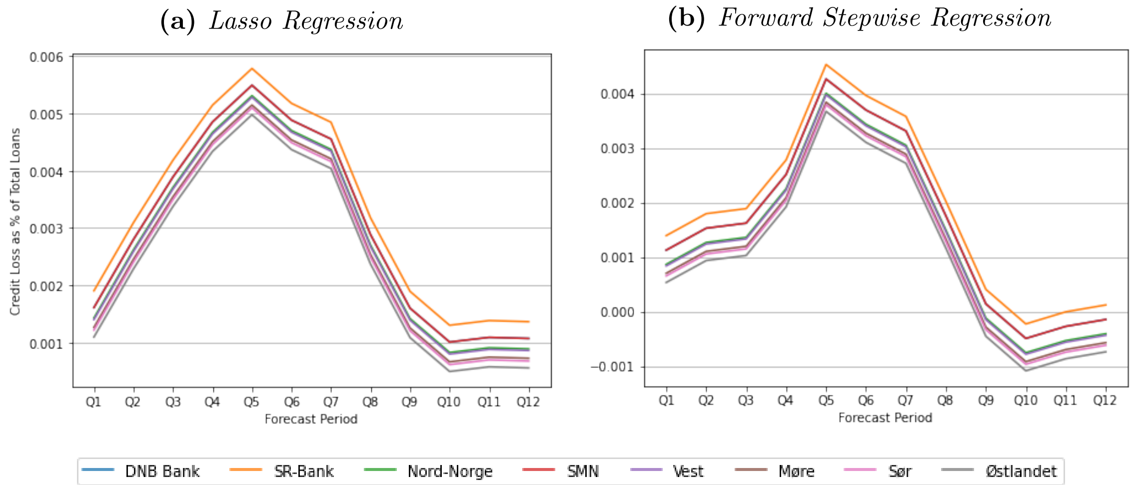


Figure 8: ***(a)*** *shows predicted quarterly losses as a percentage of Total Loans for the Forward Stepwise Regression model.* ***(b)*** *Shows predicted quarterly losses as a percentage of Total Loans for the Lasso Regression model.*

Nevertheless, the credit losses are not large enough to cause any significant fall in capital, as discussed in the previous two subsections. Compared to the banking crisis in the 90s, our forecasts of credit losses are much lower. However, system-wide credit losses of the size seen in the our scenario would be the largest in the last 25 years. A question is whether the loss rate of 4 percent of total lending seen in the banking crisis is relevant today. The economic structure is different, and banks are more restricted in lending than in the 1980s and early 1990s. The Norwegian economy is strong, with good schemes for people that become unemployed, further increasing the ability to service debt even in bad times. Different measures have also been introduced to strengthen banks' ability to minimize credit losses. Regulatory requirements for capital are stricter, and much focus has been put on improving individual banks' risk management.

For more relevant numbers in today's economy, it can be convenient to look at the sizes of credit losses the central bank of Norway employs in the stress test included in its Financial Stability Report for 2022. In the report, the projected yearly loan losses for an aggregated macro-bank over four years range from 1.1 percent to 2.2 percent of total lending. The credit losses predicted from our models are not far from these levels, but most importantly, they decrease faster in our scenario, with low credit loss rates in the last projected year. Greater rates over an extended period would possibly destroy more capital. The central bank of Norway's stress test projects a more significant reduction in GDP growth over a longer period than in our scenario, potentially explaining why our models forecasts a faster decline in losses. Another explanation is, of course, differences in models. An example is that their models may better capture the effect of a potential decline in property prices on predicted credit losses.

To assess how greater credit losses over an extended period affects the banks in our data, we conduct a sensitivity analysis consisting of two different scenarios with figures like in the two previous paragraphs. In the first scenario, the losses are projected to develop in a manner like the stress test outlined in the Financial Stability Report of 2022. In the second scenario, the losses follow a pattern like what was observed during the Norwegian banking crisis. In both scenarios, we set the value of financial instruments to zero throughout the entire period, such that this variable does not increase or decrease the capital adequacy ratio. This approach aligns with how development of financial instruments was used in the stress test of the 2014 Financial Stability Report, except for the initial decline. We further assume that net interest income develops in the same way as with the forecasts generated by the Lasso model.

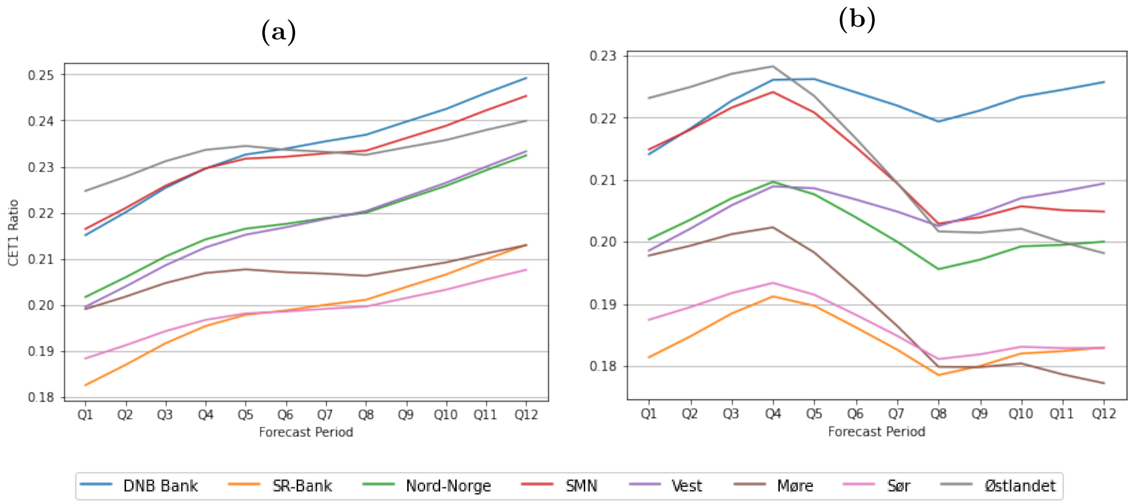


Figure 9: *(a) Shows development of CET1 Ratio in a stress scenario with Credit Losses as used in the Financial Stability Report by Norges Bank 2022b.* ***(b)*** *shows a more severe development in Credit Losses with figures from the banking crisis of the early 90s.*

With credit losses of around 1-2 percent of total lending over the stress horizon, the different banks' CET1 ratios develop as shown in figure 9a. Only two of the banks' end up with deficits in the scenario; Sparebanken Møre and SpareBank 1 Østlandet. With losses of these sizes, all banks uphold their CET1 ratio requirements as of 31.12.2022 with good margins. However, it's important to remember how other factors like other income and costs take the edge off the effect of losses in the income statements. This shows that a stress test at this level is vulnerable to small changes in other items like net provision, other costs, and such.

If we take it a step further and assume credit losses at levels that occurred during the banking crisis, SpareBank 1 Nord-Norge, SpareBank 1 SMN, Sparebanken Møre, Sparebanken Sør, and SpareBank 1 Østlandet banks suffer reductions in their CET1 ratios, as shown in 9b. Nevertheless, none of the banks breached their Pillar 1 or Pillar 2 requirements as of 31.12.2022, even though both Sparebanken Møre and SpareBank 1 Østlandet reduced their CET1 ratios of 2 percent and 2.5 percent respectively. Firstly, this shows the importance of well-capitalized banks. Referring to figure 3, if banks had CET1 ratios like those in 2008, the reductions in CET1 observed in the second scenario would have led some of the banks' capital towards the minimum requirement. With CET1 ratios at 2022 levels, Norwegian banks are better suited to withstand substantial credit losses.

Furthermore, it is also here important to keep in mind that other income figures heavily influence the outcome of each bank's income statement. Additionally, the lending-to-asset ratio of individual banks plays a significant role in how credit losses impact the CET1 ratio. For instance, consider DNB, which has a lower lending-to-asset ratio compared to Sparebanken Møre. With identical credit losses as a percentage of total lending, DNB's capital would be less affected than what would be the case for Sparebanken Møre. One must also keep in mind that the numbers presented are at the parent bank level; it may develop differently on the bank group level.

Another aspect is that we would expect that RWA will increase more than in our scenarios due to the higher credit risk. A factor reducing the CET1 ratio, according to what we have mentioned earlier. Our outcomes would in such case be too optimistic. Finally, a combined severe decline in the value of financial instruments would lead to a greater reduction in CET1 ratios as well.

Our findings from the sensitivity analysis resemble the magnitude of credit losses the central bank of Norway claims that Norwegian Banks can withstand without depleting their capital. In the last Financial Stability Report of May 2023, Norwegian Banks can withstand losses in excess of 2 percent of total lending, given that net interest income is on the same level as in 2022. The banks can cover credit losses of around 2.5 percent before they violate their capital requirements (Norges Bank 2023). We find a slightly higher tolerance for the banks in our data set, however, our projections of RWA may potentially affect these differences.

5.4 Model Evaluation

Given our accessible data, we made the decision to estimate our models using the entire data set, meaning that no observations were left for model validation and testing. As a result, it becomes hard to assess how well the models perform during a stress scenario. However, regarding goodness-of-fit, the models for net interest income exhibit the best fit, as both the Forward Stepwise Regression and the Lasso Regression yield R^2_{adj} and R^2 of over 0.8, respectively. The models for net interest income would be the easiest to test as the variables show less variation across the observations. The impact of different independent variables on net interest income is less sensitive to which period is included in the base of estimation.

In contrast, the credit loss models are very sensitive to which period it is estimated on. For instance, if the models are estimated on data that does not include

2020, the GDP does not need to have any significant impact on the development of losses. Utilizing such a model on severe macroeconomic figures would not lead to any remarkable development of credit losses. Therefore, we choose to use all data for training. The credit loss models show lower levels of goodness-of-fit, with R^2_{adj} and R^2 around 0.4. However, considering the earlier discussion on credit losses, neither of the models predicts improbable figures when compared to the stress tests conducted by the central bank of Norway or historical figures. The Forward Stepwise model predicts a substantial reduction in the value of financial instruments. Nevertheless, as argued in section 5.1, these numbers can be plausible when compared to the numbers from the Financial Stability reports. R^2_{adj} and R^2 for the models on financial instruments also show values of approximately 0.4 for the Forward Stepwise model and the Lasso model, respectively.

The data from 2013 until now represents a very good time for the Norwegian economy, even though it includes the COVID pandemic. Evaluating the predictive performance of stress test models on data that does not encompass major macroeconomic crises is challenging. Ideally, the data should contain two significant crises where banks encountered problems. The models would then be estimated on the first crisis and tested on the second. Regarding Norwegian data, one should have data from the banking crisis in the 1990s included in the base of estimation. There are, fortunately, no other significant periods with banking problems in Norway, making it hard to evaluate the predictive performance of stress testing models on Norwegian banks, even though the banking crisis is included in the estimation of models.

6 Conclusion

In this paper, we gain comprehensive insight into the performance of the Norwegian banking sector under a stress scenario using two statistical models: Forward Stepwise Regression and Lasso Regression. By comparing the outcome of these models, combined with the sensitivity analysis on credit losses, we have not only enhanced our understanding of the strengths and limitations of each method but also provided valuable insights into the resilience of the Norwegian financial system. Our research corroborates the assertion made by the Central Bank of Norway, suggesting that the Norwegian financial system exhibits robustness when evaluated through a Top-down stress test.

By constructing a scenario based on the combination of data from the GFC, the Norwegian Banking Crisis, and numbers used in the Central Bank of Norway's stress test in the 2022 Financial Stability Report, we argue that our setting for a crisis is plausible.

Our findings reveal that both models offer advantages in stress testing when there is uncertainty about which explanatory variables to include in the models. The Lasso Regression model projects a decline in profit but no deficits through the stress scenario. The Forward Stepwise Regression predicts that five banks will experience deficits through two periods, with DNB obtaining the greatest loss. Regarding the analysis of credit losses, both models provide relatively similar results but differ in the projection of the Value of financial instruments. Most importantly, none of the banks breach the capital requirement in the scenarios utilizing the models or in the sensitivity analysis on credit losses.

By applying these methods to the Norwegian banking sector, we highlight the importance of regulatory oversight and risk management strategies in mitigating systemic risks. Our analysis also emphasizes the need for banks to maintain sufficient capital buffers and improve their risk management practices to withstand adverse economic conditions. Furthermore, the study sheds light on the importance of choosing appropriate models for stress testing. It demonstrates that adopting multiple methods can provide a more comprehensive understanding of potential risks in the banking sector.

6.1 Further Work

Since the estimated models are utilized on a designed stress scenario, which involves a degree of speculation, this study does not focus on comparing the predictive capabilities of the Forward Stepwise Regression and Lasso Regression models. Instead, the models are applied as a part of a broader method to stress test the Norwegian banking sector on a hypothetical scenario. Further work would thus involve finding a better way to examine the predictive performance of estimated models on Norwegian banks.

The importance of macroeconomic scenarios in stress-testing banks is also worth considering. When we employ relatively simple macroeconomic modeling, as in our stress tests, we cannot be sure that the development of different macroeconomic indicators will align precisely with our predefined scenarios. There may be more detailed and dynamic connections among macroeconomic variables, for example between the GDP and the unemployment rate. The macro scenarios utilized by authorities, like the Central Bank of Norway, may thus be more dynamic than ours. Further work should involve a more dynamic approach to designing the macro scenarios. More extensive testing of various performance measures directly can also provide valuable insights. For example, assessing the losses a bank can withstand over an extended period without incorporating macroeconomic variables could offer a different perspective on a bank's resilience. We are also aware that if our results would consist of major losses for the largest banks in Norway, it would either be a severe problem with the banking sector or our models would be flawed, where the former may be the worst scenario.

Further work includes a more dynamic approach to testing banks' balance sheets and income statements. Some newer papers have started implementing Neural Networks to impose a dynamic structure in the stress testing approach, which can model the nonlinearities of a complex balance sheet. However, we are unaware of such methods being implemented in the Norwegian sector; a reason may be the black box problem that arises with such machine learning methods, although this problem is now alleviated by using explainable AI (XAI) techniques. Regarding dynamic balance sheets, stress testing behavioral effects on banks' balance sheets will be relevant in the future. Stress tests that focus on, for example, bank-runs, like what one saw for some American banks during spring 2023, can be an area where it is essential to understand the underlying risks.

Bibliography

Andersen, Henrik and Tor Oddvar Berge (2008). 'Stress testing of banks' profit and capital adequacy'. In: *Norges Banks Economic Bulletin* 2, p. 52.

Andersen, Henrik and Ragnar Enger Juelsrud (2022). 'Optimal capital adequacy ratio for Norwegian banks'. In: *STAFF MEMO* 9/2022, p. 37.

Baudino, Patrizia et al. (2018). 'Stress-testing banks - a comparative analysis'. In: 12, p. 36.

BIS (2019). *History of the Basel Committee*. URL: https://www.bis.org/bcbs/history.htm. (accessed: 17.4.2023).

Brooks, Chris (2019). eng. University Printing House, Cambridge CB2 8BS, United Kingdom: Cambridge University Press, p. 438. ISBN: 9781108422536.

Casellina, Simone, Giuseppe Pandolfo and Mario Quagliariello (2020). 'APPLYING THE PRECOMMITMENT APPROACH TO BOTTOM-UP STRESS TESTS: A NEW OLD STORY'. In: *EBA STAFF PAPER SERIES* 5.

Chan, Jireh Yi-Le et al. (2022). 'Mitigating the Multicollinearity Problem and Its Machine Learning Approach: A Review'. In: *Mathematics* 10.8. ISSN: 2227-7390. DOI: 10.3390/math10081283. URL: https://www.mdpi.com/2227-7390/10/8/1283.

Chan-Lau, Jorge A. (2017). 'Lasso Regressions and Forecasting Models in Applied Stress Testing'. In: *IMF Working Paper*.

Choi, Candice (2023). *The Banking Crisis: A Timeline of Silicon Valley Bank's Collapse and Other Key Events*. URL: https://www.wsj.com/articles/bank-collapse-crisis-timeline-724f6458?st=l13smszoeiysisa&reflink=desktopwebshare_permalink. (accessed: 12.04.2023).

Čihák, Martin (2007). 'Introduction to Applied Stress Testing'. In: IMF Working Paper No. 07/59, p. 76.

Collischon, Matthias and Andreas Eberl (2020). 'Let's Talk About Fixed Effects: Let's Talk About All the Good Things and the Bad Things'. In: *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie* 72.2, pp. 289–299.

Das, Udaibir, Kieran Dent and Miguel Segoviano (2022). 'Fit for Purpose? The Evolving Role of Stress Testing for Financial Systems'. In: *Handbook of Financial Stress Testing*. Ed. by J. Doyne Farmer et al. Cambridge University Press, pp. 32–46. DOI: 10.1017/9781108903011.005.

Dent, Kieran, Ben Westwood and Miguel Segoviano Basurto (2016). 'Stress Testing of Banks: An Introduction'. In: *Bank of England Quarterly Bulletin*, pp. 130–143.

FED, Board of Governors of the Federal Reserve System (2009). 'The Supervisory Capital Assessment Program: Design and Implementation'. In.

Finans Norge (2023). *Bankstatestikk.* URL: https://www.finansnorge.no/tema/statistikk-og-analyse/bank/ (visited on 15th May 2023).

Finanstilsynet (2022a). *Bank og finans.* URL: https://www.finanstilsynet.no/forbrukerinformasjon/bank-og-finans/. (accessed: 20.4.2023).

— (2022b). *Beregningsgrunnlaget.* URL: https://www.finanstilsynet.no/tema/kapitaldekning/beregningsgrunnlaget/. (accessed: 30.4.2023).

— (2022c). *Kapitaldekning.* URL: https://www.finanstilsynet.no/tema/kapitaldekning/. (accessed: 21.4.2023).

— (2022d). *Likviditet.* URL: https://www.finanstilsynet.no/tema/likviditet/. (accessed: 11.5.2023).

— (2022e). *Vurdering av samlet kapitalbehov og tilsynsmessig oppfølging (pilar 2).* URL: https://www.finanstilsynet.no/tema/kapitaldekning/vurdering-av-samlet-kapitalbehov-og-tilsynsmessig-oppfolging-pilar-2/. (accessed: 21.4.2023).

Herring, Richard J. and Til Schuermann (2022). 'Objectives and Challenges of Stress Testing'. In: *Handbook of Financial Stress Testing.* Ed. by J. Doyne Farmer et al. Cambridge University Press, pp. 9–31. DOI: 10.1017/9781108903011.004.

International Monetary Fund (2023). *Financial Sector Assessment Program (FSAP).* URL: https://www.imf.org/en/Publications/fssa (visited on 19th Apr. 2023).

Lund, Arild J. and Mari Aasgaard Walle (2019). *Hvor stor er norsk banksektor? En internasjonal sammenligning.* URL: https://www.norges-bank.no/bankplassen/arkiv/2019/hvor-stor-er-norsk-banksektor-en-internasjonal-sammenligning/. (accessed: 20.4.2023).

Norges Bank (2022a). *Det norske finansielle systemet.* URL: https://www.norges-bank.no/aktuelt/nyheter-og-hendelser/Publikasjoner/det-norske-finansielle-systemet/2022-dnfs/innhold/. (accessed: 20.4.2023).

— (2022b). *Financial Stability Report 2022: vulnerabilities and risks.* Tech. rep. ISSN 1503-8858. Bankplassen 2, Oslo: Norges bank.

— (2023). *Finansiell stabilitet 2023 - 1. halvår.* ISSN 1503-884X. Norges Bank, p. 39.

Pengepolitisk Rapport (2021). *Pengepolitisk rapport med vurdering av finansiell stabilitet 4/2021.* ISSN 1894-0234. Norges Bank.

Skrede, Magnus, Ørjan Glesnes and Kjell Ove Røsok (2022). *Tapsavsetninger i norske banker basert på IFRS 9 under koronaen (F).* URL: https://nye.econa.no/faglig-oppdatering/medlemsbladet-magma/5-2022/tapsavsetninger-i-norske-banker-basert-pa-ifrs-9-under-koronaen-f. (accessed: 30.4.2023).

Sørensen, Kasper Kragh and Haakon Solheim (2014). 'Hva taper bankene penger på under kriser?' In: *Staff Memo* 3.

Statistics Norway (2023a). *Arbeidsledighet i Norge*. URL: https://www.ssb.no/arbeid-og-lonn/sysselsetting/artikler/arbeidsledighet-i-norge. (accessed: 19.4.2023).

— (2023b). *Fakta om norsk økonomi*. URL: https://www.ssb.no/nasjonalregnskap-og-konjunkturer/faktaside/norsk-okonomi. (accessed: 19.4.2023).

— (2023c). *Konsumprisindeksen*. URL: https://www.ssb.no/priser-og-prisindekser/konsumpriser/statistikk/konsumprisindeksen. (accessed: 19.4.2023).

— (2023d). *Kredittindikator*. URL: https://www.ssb.no/bank-og-finansmarked/finansielle-indikatorer/statistikk/kredittindikator. (accessed: 19.4.2023).

SVB Financial Group (2023). *SVB Financial Group Announces Proposed Offerings of Common Stock and Mandatory Convertible Preferred Stock*. URL: https://ir.svb.com/news-and-research/news/news-details/2023/SVB-Financial-Group-Announces-Proposed-Offerings-of-Common-Stock-and-Mandatory-Convertible-Preferred-Stock/default.aspx. (accessed: 12.04.2023).

Syversten, Bjørne Dyre et al. (2015). 'Bankmodellen og stresstesten i rapport om Finansiell stabilitet 2015'. In: *Staff Memo* 5.

Tibshirani, Robert (2011). 'Regression shrinkage and selection via the lasso: a retrospective'. In: *Journal of the Royal Statistic Society*, pp. 273–282.

Wooldridge, Jeffrey M. (2020). *Introductory Econometrics: A Modern Approach*. Cengage. ISBN: 9781337558860.

Appendix

A Bank Specific Variables Included in Final Data set

Balance sheet	**Income statement**
Cash and deposits with central banks	Interest income
Due from credit institutions	Interest expenses
Loans to customers	Net interest income
Total loans before impairments	Dividends etc.
Write-downs on individual loans	Commissions and fees receivable
Write-downs on groups of loans	Commission and fees receivable from credit institutions
Certificates, bonds, and securities	Other fees and commission income incl. guarantee commission
Shares, holdings and other securities	Commissions and fees payable
Shares and equity certificates	Net gain on foreign exchange and financial instruments
Investments in associated companies	Other operating income
Investments in subsidiaries	Commission income from mortgage companies
Intangible assets	Other operating revenues
Fixed assets	Net other operating income
Other assets	Total operating revenues
Prepaid unincurred costs	Salaries and general administrative expenses
TOTAL ASSETS	Salaries and social costs
Due to credit institutions	Administrative costs
Deposits from customers	Depreciation, appreciation etc.
Debt securities issued	Other operating expenses
Other liabilities	Total operating expenses
Incurred expenses and liabilities	Operating profit before losses
Subordinated loan capital	Losses on loans, guarantees, etc.
Total liabilities	Loan losses
Paid-in capital	Loss of guarantees, etc.
Retained earnings	Profit before tax
Total equity	Tax
TOTAL LIABILITIES AND EQUITY	Profit for the accounting period

Table 3: *List of all variables included in our dataset.*

B Coefficients from Lasso Regression

	Lending	Deposits	NIBOR	OIL	10YR	UR	GDP	OSEBX	HP	K2	CPI
t	0.00054	0.00332	0.02299	0.00000	-0.00031	-0.00227	0.00000	0.00000	-0.01116	0.00000	-0.01205
t-1	0.00000	0.00124	-0.03286	0.00000	-0.00285	-0.00307	0.00000	0.00000	0.00000	0.00000	0.00615
t-2			0.00000	0.00000	0.00000	-0.00355	0.00000	-0.00114	-0.00148	0.00000	0.01703
t-3			0.00000	0.00000	0.00000	-0.00973	-0.00605	-0.00228	0.00000	-0.01796	-0.00228
t-4			-0.00123	-0.00005	0.00000	-0.00114	-0.00029	-0.00171	-0.00159	0.00000	0.00000

Table 4: *Lasso coefficients: Net interest income*

	NIBOR	OIL	10YR	UR	GDP	OSEBX	HP	K2	CPI
t	-0.01411	-0.00000	0.00000	0.00164	-0.01020	0.00780	0.02943	-0.01070	-0.06997
t-1	0.00000	0.00018	0.00000	0.00000	0.00000	0.00053	-0.02613	0.00000	0.00000
t-2	0.00000	0.00000	0.07652	0.00000	-0.00442	-0.00239	0.00000	0.00000	0.00789
t-3	0.00000	-0.00030	-0.05949	0.00000	-0.00494	-0.00023	0.00000	0.00000	0.06633
t-4	0.00000	0.00025	0.00000	0.00000	0.00074	0.00000	-0.01451	-0.01446	0.03008

Table 5: *Lasso coefficients: Financial instruments*

	NIBOR	OIL	10YR	UR	GDP	OSEBX	HP	K2	CPI
t	0.00000	0.00000	-0.00741	0.00000	-0.01259	-0.00142	0.00000	-0.02245	-0.00881
t-1	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00482	-0.03074	0.00000
t-2	0.02191	0.00006	0.00000	0.00000	-0.00161	0.00000	0.00000	-0.04452	0.00000
t-3	0.02962	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00465
t-4	0.00000	0.00000	-0.00937	0.00000	0.00000	0.00000	0.00000	0.03045	0.00000

Table 6: *Lasso coefficients: Credit losses*

C Coefficients from Forward Stepwise Regression

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0014	0.0003	5.43	0.0000
Deposits_{t-1}	0.0008	0.0010	0.81	0.4186
NIBOR_{t}	0.0491	0.0049	10.06	0.0000
10YR_{t}	-0.0132	0.0090	-1.47	0.1420
Østlandet	-0.0005	0.0001	-9.24	0.0000
Sør	-0.0004	0.0001	-8.59	0.0000
SMN	-0.0005	0.0001	-6.75	0.0000
Lending_{t}	0.0026	0.0007	3.93	0.0001
HP_{t}	-0.0218	0.0046	-4.76	0.0000
Deposits_{t}	0.0030	0.0010	2.97	0.0032
10YR_{t-1}	-0.0176	0.0094	-1.86	0.0635
UR_{t-3}	-0.0077	0.0024	-3.15	0.0018
HP_{t-4}	-0.0117	0.0037	-3.15	0.0018
CPI_{t-2}	0.0397	0.0095	4.19	0.0000
OIL_{t-4}	-0.0002	0.0001	-2.30	0.0222
OIL_{t-1}	0.0003	0.0001	3.25	0.0013
HP_{t-1}	-0.0109	0.0045	-2.44	0.0154
Lending_{t-1}	-0.0012	0.0006	-1.80	0.0736
Nord	-0.0001	0.0001	-2.79	0.0057
SR	-0.0002	0.0001	-2.26	0.0247
OIL_{t}	0.0002	0.0001	1.72	0.0866
K2_{t-3}	-0.0187	0.0119	-1.58	0.1164
NIBOR_{t-1}	-0.0208	0.0153	-1.36	0.1750
Observations	288			
R^2	0.851			
Adjusted R^2	0.839			
Residual σ_M	0.0002 (df = 265)			
F Statistic	68.979*** (df = 22; 265)			
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 7: *Forward Stepwise Regression net interest income. Note that HP, CPI, and K2 is the first difference of their logs.*

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0016	0.0004	3.92	0.0001
OSEBX	0.0092	0.0020	4.57	0.0000
HP_{t-1}	-0.0274	0.0114	-2.41	0.0165
HP_{t-4}	-0.0320	0.0097	-3.31	0.0011
CPI_{t-3}	0.0724	0.0236	3.07	0.0024
UR_t	0.0160	0.0066	2.44	0.0155
OIL_{t-4}	0.0004	0.0003	1.70	0.0895
CPI_t	-0.1587	0.0221	-7.17	0.0000
HP_t	0.0581	0.0116	4.99	0.0000
$10YR_{t-1}$	0.0058	0.0139	0.42	0.6775
$10YR_{t-3}$	-0.1460	0.0218	-6.71	0.0000
$10YR_{t-2}$	0.1603	0.0273	5.88	0.0000
OIL_{t-3}	-0.0009	0.0003	-3.17	0.0017
OIL_{t-2}	-0.0006	0.0004	-1.48	0.1391
OIL_t	0.0001	0.0003	0.29	0.7747
SR	-0.0004	0.0001	-4.19	0.0000
SMN	-0.0004	0.0001	-4.18	0.0000
$OSEBX_{t-2}$	-0.0058	0.0024	-2.37	0.0187
$NIBOR_{t-2}$	-0.1239	0.0368	-3.36	0.0009
UR_{t-2}	-0.0351	0.0117	-3.01	0.0029
$NIBOR_{t-3}$	0.0638	0.0414	1.54	0.1243
HP_{t-2}	0.0275	0.0103	2.67	0.0080
Østlandet	-0.0004	0.0001	-3.60	0.0004
Sør	-0.0004	0.0001	-3.58	0.0004
GDP_{t-4}	0.0170	0.0082	2.08	0.0386
GDP_{t-3}	0.0107	0.0071	1.50	0.1356
Nord	-0.0003	0.0001	-2.86	0.0046
Vest	-0.0003	0.0001	-2.62	0.0092
Møre	-0.0003	0.0001	-2.52	0.0125
Observations	288			
R^2	0.484			
Adjusted R^2	0.428			
Residual σ_M	0.0004 (df = 259)			
F Statistic	8.664*** (df = 28; 259)			

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: *Forward Stepwise Regression: Financial instruments. Note that HP, CPI, GDP, OSEBX, and K2 is the first difference of their logs.*

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0000	0.0001	0.19	0.8519
NIBOR_{t-3}	0.0378	0.0114	3.31	0.0011
SR	0.0004	0.0001	5.87	0.0000
GDP_t	-0.0210	0.0040	-5.28	0.0000
10YR_{t-4}	-0.0383	0.0068	-5.67	0.0000
SMN	0.0002	0.0001	2.90	0.0040
HP_{t-1}	0.0248	0.0057	4.35	0.0000
NIBOR_{t-2}	0.0408	0.0120	3.41	0.0007
Østlandet	-0.0002	0.0001	-2.40	0.0168
HP_{t-3}	-0.0120	0.0055	-2.18	0.0301
CPI_t	-0.0180	0.0116	-1.56	0.1203
Observations	288			
R^2	0.400			
Adjusted R^2	0.378			
Residual σ_M	0.0004 (df = 277)			
F Statistic	18.448*** (df = 10; 277)			
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 9: *Forward Stepwise Regression: Credit losses. Note that HP, CPI, and GDP is the first difference of their logs.*

D Yearly Credit Losses

	DNB	SR-Bank	Nord-Norge	SMN	Vest	Møre	Sør	Østlandet
Year 1	0,89	0,90	0,49	0,67	0,57	0,48	0,52	0,39
Year 2	1,92	1,60	1,00	1,29	1,23	1,03	1,10	0,95
Year 3	-0,30	0,01	-0,16	-0,05	-0,19	-0,16	-0,17	-0,26

Table 10: *Predicted yearly losses as percentage of Total loans, foward stepwise regression model*

	DNB	SR-Bank	Nord-Norge	SMN	Vest	Møre	Sør	Østlandet
Year 1	1,56	1,31	0,86	1,00	1,00	0,81	0,86	0,75
Year 2	1,90	1,55	1,05	1,24	1,22	1,00	1,06	0,94
Year 3	0,31	0,47	0,17	0,28	0,20	0,14	0,14	0,07

Table 11: *Predicted yearly losses as percentage of Total loans, Lasso Regression model.*

NTNU

Norwegian University of
Science and Technology