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A VAR Quantile Regression Analysis of Credit Losses in Norway*

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Abstract

Credit losses are the primary driver of large fluctuations in bank earnings and capital, often spiking sharply during periods of economic stress. In this Memo, we analyse the link between macroeconomic conditions and aggregate credit losses for large Norwegian banks, explicitly addressing model uncertainty within a VAR framework. We focus on tail-risk dynamics and find that the short-term upside risk of credit losses relative to total assets is largely driven by inflation and policy rate shocks. These shocks presumably increase borrowing costs and weaken economic activity, intensifying financial strain on households and firms. By capturing nonlinear effects and accounting for model uncertainty, our findings provide valuable insights for stress test calibration and macroprudential policy design.

1 Introduction and summary

Banking crises are costly and typically associated with significant credit losses. Unlike other bank expenses, credit losses are more volatile, and infrequent, but wide fluctuations materially impact bank earnings (Chart 1). As credit losses are both a symptom and a possible cause of deteriorating economic conditions, it is important to understand how this key cost component relates to general macroeconomic conditions.

The pandemic highlighted the need for real-time assessments of financial stability. A leading concern was that banks could tighten credit and worsen the economic downturn in the event

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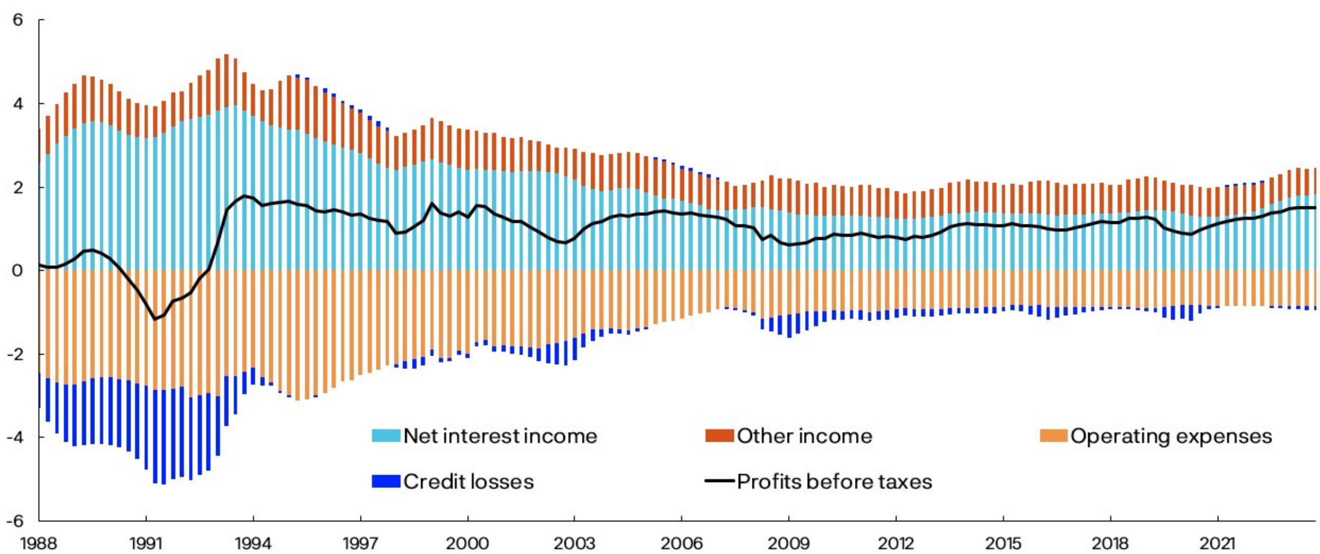
of high credit losses. Mitigating measures, such as the reduction of the countercyclical capital buffer, were implemented in spring 2020.[1] Although Norwegian banks were considered robust at the onset of the crisis and supported by mitigating measures, analysing developments in credit losses during 2020 remained essential for assessing the health of the banking sector and for fine-tuning prudential measures. In the post-pandemic period, rising interest expenses, weak economic growth, and geopolitical tensions led to renewed concerns about increasing credit losses, yet now credit losses remained low. It is of interest to identify the driving forces behind this deviation from expectations, to improve our understanding of the dynamics of credit losses going forward.

Chart 1: *Historical decomposition of banks' pre-tax earnings. As a share of average total assets. Percent. The bars show contributions from banks' income and cost components*



Annualised and break-adjusted time series for the sum of seven large Norwegian banks. Banks' operating expenses and credit losses are reported with a negative sign.
Sources: S&P Capital IQ and Norges Bank

Stress testing has become an increasingly important tool in many jurisdictions for evaluating whether banks have adequate capital coverage and can also serve as a valuable instrument in the calibration of macroprudential tools (Bennani et al. (2017) and Andersen et al. (2019)) and in crisis management strategies (Borio et al. (2014)). A key component of stress-testing frameworks are satellite models that connect adverse macroeconomic scenarios to the evolution of banks' credit losses. Ideally, such satellite models should effectively capture the sharp increase in credit losses that occur during periods of system-wide stress. However, accurately modelling this nonlinear effect is challenging, largely due to the limited availability of historical data on banking crises.

An approach to addressing this limitation is incorporating international data (Hardy and Schmieder (2013), Hardy and Schmieder (2020) and Ong et al. (2023)), although critics may

[1]See Norges Bank reduces the policy rate, provides liquidity and advises the Ministry of Finance to reduce the countercyclical capital buffer.

argue that such crises may not fully reflect the specific characteristics of the Norwegian economy.

Depending on a single model can create a false sense of security, even if the model appears well-specified according to traditional criteria. This is especially relevant when using Norwegian data, which reflects the experience of only one severe banking crisis. Gross and Poblacion (2017) emphasise the importance of addressing model uncertainty, demonstrating that, for 75 large European banks, many plausible models fit the historical data, yet their scenario-based projections can differ substantially. In the 2020 FSAP[2] stress test of Norwegian banks, the IMF (2020) applied the same methodology to project non-performing loans in 17 key industries. By accounting for model uncertainty when estimating credit risk, they show that the adverse scenarios have a significant negative impact on banks' capital ratios.

In this Memo, we examine the link between the macroeconomy and aggregate credit losses for seven large Norwegian banks[3], relative to the sum of their average total assets (ATA). Our starting point is a linear VAR model covering the period since the Norwegian banking crisis, where we focus on general macroeconomic drivers such as aggregate economic activity, inflation, the policy rate and the real exchange rate. Our findings are broadly in line with the existing (linear) literature, confirming a negative correlation between economic activity indicators and credit losses, regardless of the type of shocks considered.

While the *sign* of the estimated credit loss responses is broadly in line with the literature, it is important to acknowledge that the *size* is relatively moderate. The historical shock decomposition also reveals that credit loss spikes are mostly driven by shocks to credit losses themselves, meaning that they are mostly unexplained. As a policy institution performing stress test exercises and crisis management, our main interest is in understanding the macroeconomic conditions that drive spikes in credit losses. Even though our model is well specified according to several traditional criteria, we challenge our starting point along several dimensions.

We begin by expanding the framework with a longer dataset, by including the Norwegian banking crisis (1988-93), and a variety of financial variables. To also capture the effect of the macrodynamics leading up to the Norwegian banking crisis and as it unfolds, we use a break-adjusted time series back to the end of 1981. To isolate the impact of each expansion of the model, we estimate a range of models. Although the richer frameworks often provide better explanations for certain spikes, they tend to perform worse across the rest of the sample, leaving a substantial portion of the spikes unexplained (in VAR-terminology, the unexplained part is referred to as "shocks to credit losses").

In the last step, to better understand the dynamics of credit loss peaks, we perform an in-depth analysis using quantile regressions. We shift our attention from the expected mean of credit losses to the entire distribution. By applying this flexible approach, we investigate whether credit

[2]Financial Sector Assessment Programme.

[3]The large Norwegian banks are DNB Bank, SpareBank 1 SR-Bank, Sparebanken Vest, SpareBank 1 SMN, Sparebanken Sør, SpareBank 1 Østlandet and SpareBank 1 Nord-Norge.

loss peaks (measured by the 95th percentile) react differently to macroeconomic shocks than the more common losses (measured by the median) that most studies focus on. In our analysis, we focus on the short-term upside risk (the difference between the 95th percentile and the median) and how it relates to the macroeconomic shocks identified in our linear VAR model. We believe a relatively short time horizon is appropriate, as policymakers are concerned with the impact of current economic deterioration on near-term credit loss spikes. This is especially relevant in stress tests, where the focus is on projecting the severity of an immediate tail event.

Our main findings are related to this nonlinear approach: Quantile regression reveals that the short-term upside risk of high credit losses increases both significantly and *substantially* in response to positive shocks to inflation and the policy rate. Both shocks result in a combination of increased interest expenses and deteriorating economic activity. Our interpretation is that this adverse combination exacerbates the financial strain on firms and households, leaving them more vulnerable to systemic stress when it occurs. In contrast, a negative shock to GDP growth is alleviated by a lower policy rate that positively affects both the recovery of the economy and bank customers' ability to service their debt. This combination likely explains the unchanged or decreasing upside risk one year in advance.

Although this framework does not help us pinpoint the exact timing of realised credit loss spikes, it provides valuable insights by linking the macroeconomic environment to the severity of these spikes when they materialise. The historical one-year-ahead forecast distribution of credit losses indicates that the short-term upside risk of credit losses was elevated in the periods preceding the Norwegian banking crisis, the 2002-2003 peak and the financial crisis. A shock decomposition highlights inflationary pressures and unexpected interest rate changes as key drivers of historical changes in upside risk. Finally, we show that a stress-testing exercise that is meant to capture system-wide risk can utilise the predicted tail of the credit loss distribution as a valuable benchmark for assessing severity.

We acknowledge that several factors, including idiosyncratic bank-specific elements such as risk management, fraud exposure, geographic factors, and industry profiles, influence credit losses. However, this study focuses on common factors across banks (e.g. macroeconomic developments). Over time, structural changes, improvements in risk management, changes in risk exposure, and evolving accounting frameworks have also likely influenced credit losses, which may make the relationship between macroeconomic developments and credit losses less stable. In addition, the macroeconomic environment has changed, for example with the introduction of the inflation targeting regime in 1999.[4] Also, the capacity for fiscal policy in Norway to act as a buffer has increased significantly over time. Nonetheless, our model, supported by extensive robustness checks, demonstrates satisfactory empirical properties and we believe the analyses offer important insights.

The remainder of this Memo is organised as follows. Section 2 presents an introductory technical

[4]Inflation targeting is considered to have been introduced de facto in 1999, but formally it was introduced in March 2001 (Alstadheim (2016)).

background on how credit losses are calculated. Section 3 reviews the relevant literature on the relationship between macroeconomic conditions and bank credit losses. Sections 4 and 5 outline our econometric approach and data sources, respectively. The results of our analysis are discussed in Section 6, while Section 7 uses these findings to conduct policy exercises. Finally, Section 8 offers concluding remarks.

2 What are credit losses?

Several measures capture the credit risk on banks' balance sheets. For our econometric analysis, we use annualised quarterly recognised credit losses as a percentage of banks' ATA. These recognised credit losses, recorded in banks' income statements, represent the amounts charged during the period, directly impacting banks' earnings. In addition, they broadly reflect all costs associated with *changes in credit risk* on banks' balance sheets.

Accounting standards govern the timing of the recognition of credit losses. Recognised credit losses generally consist of both *expected* and *unexpected* (actual) losses on a bank's loans. Under the current accounting standard, International Financial Reporting Standard (IFRS) 9, credit losses are required to be forward-looking by recognising *expected* credit losses. The estimated credit risk for each loan is determined by three components: 1) Probability of Default (PD), 2) Loss Given Default (LGD), and 3) Exposure at Default (EAD). *Expected* credit losses reflect the change each period in the total estimated credit risk on banks' balance sheets. If the total estimated credit risk is reduced owing to an improvement in credit quality (not write-offs), then recognised *expected* credit losses for the period are negative. These reversals usually happen when banks overestimate credit risk at the onset of a downturn, see periods with negative credit losses (positive bars) in Chart 1.

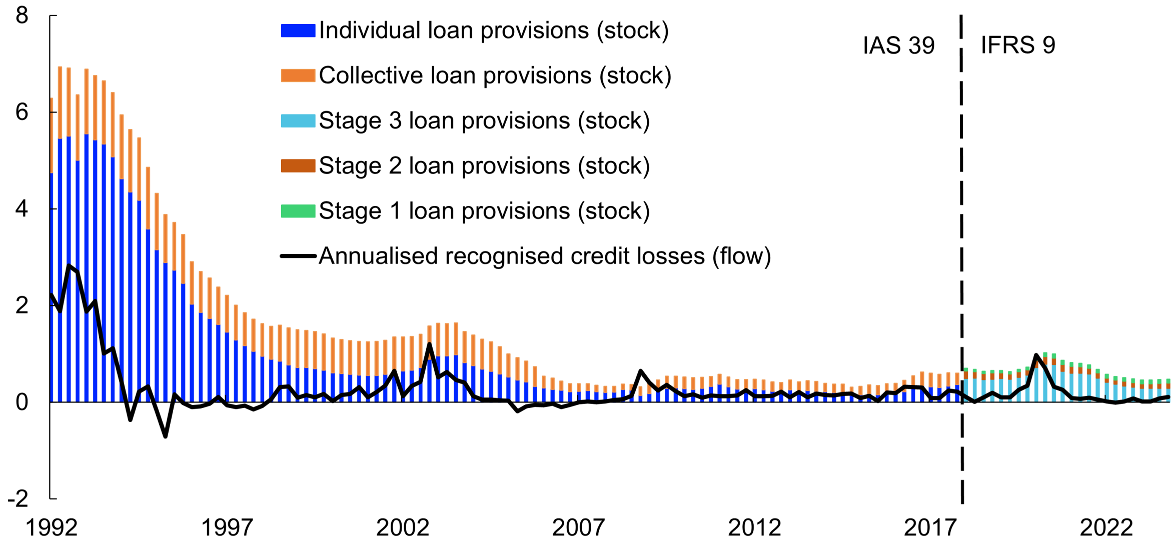
Expected credit losses may be realised as actual losses in the future, leading to the loan being written off the bank's balance sheet.[5] If the actual loss is already covered by previously recognised *expected* losses, the bank's income statement remains unaffected by the write-off. However, if the actual credit loss exceeds or falls short of the expected credit loss, the recognised credit losses in the income statement will increase or decrease accordingly, reflecting the *unexpected* credit loss.

Over time, credit losses have been determined by evolving accounting standards, leading to structural changes in their level and dynamics. A new accounting standard, IFRS 9, for impairment recognition was introduced in 2018. Under the new rules, expected credit losses are based on more forward-looking assessments, compared to the previous accounting standard, IAS 39. The former rules only gave banks the right (and obligation) to write down the value of a loan when there was objective evidence of a loss event. In addition to objective evidence, IRFS 9 relies on banks' own criteria to determine whether assets have undergone a "significant increase in credit risk". Under

[5] Actual losses are realised and loans are written off when it is highly likely that losses are final, for example upon final liquidation of a company or settlement of an estate following death.

IRFS 9, banks must recognise expected credit losses on these risky loans over the entire life of the loan. For Norwegian banks, Andersen and Hjelseth (2019) performed a counterfactual analysis calculating credit losses under both accounting standards in the period 2010-2017. Their results suggest that IFRS 9 can increase credit losses both immediately prior to and during periods of increased credit risk.

Chart 2: *The stock of banks' loan loss provisions and the flow of credit losses under different accounting regimes*



All banks and mortgage companies in Norway. Measured as share of gross lending. Some banks continued to apply IAS 39 in 2018–2019. For these banks the Norwegian banking statistics (ORBOF) included a simple mapping to IFRS 9. From 2020 onwards, all banks have applied IFRS 9.
Under ***IFRS 9****, all loans must be classified in one of three stages:*
Stage 1*: Performing loans with no significant increase in credit risk. Expected losses are over the next 12 months.*
Stage 2*: Loans with significant increase in credit risk, but there is no objective evidence of impairment. Expected losses are over the lifetime of the loan.*
Stage 3*: Loans with significant increase in credit risk, and there are objective evidence of impairment. Expected losses are over the lifetime of the loan.*
Under ***IAS 39*** *there are two types of loan loss provisions:*
Individual *LLPs are linked to specific assets.*
Collective *LLPs are often linked to risky sectors where banks expect losses to occur, but do not yet know which customers will be the source of the losses.*
Sources: For stage 1–3: E&Y (2017): "Financial Instruments: A summary of IFRS 9 and its effects". March 2017. Statistics Norway and Norges Bank

In our present historical study, we assume that the aggregate credit loss series for the seven large Norwegian banks can be considered continuous, without accounting for any change in the accounting regime. Historically, loan loss provisions (LLPs) on banks' balance sheet[6] related to objective evidence have largely driven developments in Norwegian banks' credit losses under all

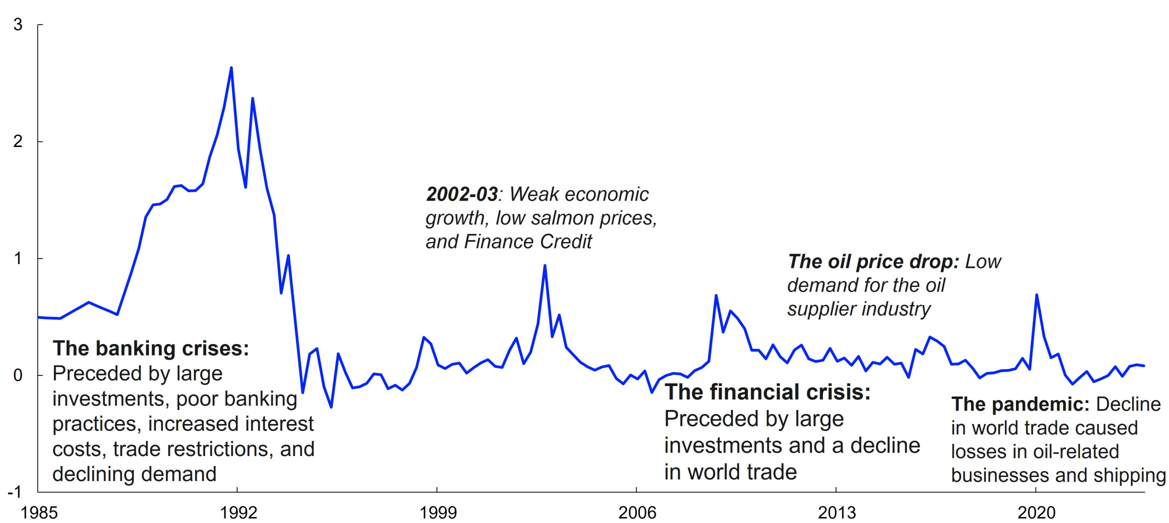
[6]While losses recorded in banks' income statements (recognised credit losses) express the amount to be charged against the accounts for the period, the stock of loan loss provisions on the balance sheet provides an indication of what banks expect to lose on their loan portfolios. Broadly speaking, the stock of LLPs reflects the total level of estimated credit risk currently on banks' balance sheets, while the recognised *expected* credit losses reflect the change in the estimated credit risk. For more information, see Norges Bank Financial Stability Report 2024 H1, page 23.

accounting standards in our sample (Chart 2). This is captured by stage 3 LLPs under IFRS 9 and individual LLPs under IAS 39 and Norwegian Accounting Standards, see Chart 2.[7] The implementation of IFRS 9 also had limited effects on the level of LLPs. However, the small change can be attributed to the low estimated credit risk of Norwegian banks when IFRS 9 was introduced. Furthermore, the largest post-2018 increase in credit risk, observed during the pandemic, was unexpected and quickly reversed. However, in the future, the IRFS 9 accounting standard may alter the dynamics of credit losses, potentially making them more cyclical than suggested by our historical analysis.[8]

3 Literature review

This section presents a focused overview of the theoretical and empirical literature on the key drivers of credit losses. This review forms the basis for selecting the variables included in our empirical model in Section 4. The evolution of banks' credit losses is directly linked to changes in customers' ability and willingness to service their debt. Over time, various aspects of economic developments are expected to influence these factors, as illustrated historically in Chart 3. In addition, the composition of banks' lending portfolios, collateral values and banks' credit practices are also likely to play a significant role in shaping the dynamics of credit losses.

Chart 3: *Historical credit loss peaks have different causes*



Annualised and break-adjusted time series for the sum of seven large Norwegian banks. As a share of ATA. Percent. Banks' credit losses are reported with a positive sign.
Sources: Andersen (2023), S&P Capital IQ, Norges Bank and OECD

[7] IAS 39 was introduced for Norwegian banks as part of the transition to the IFRS in 2005. Before this, Norwegian banks followed the Norwegian Accounting Standards for loss provisions.

[8] Beyond IFRS 9's ECL framework, earlier changes in accounting standards also shaped how banks recognised credit losses. For an overview of pre-2005 rules, see Appendix 3 in Andersen and Winje (2017). Such shifts in the accounting regime may reduce time-series comparability and, by extension, the relevance and parameter stability of our regressions.

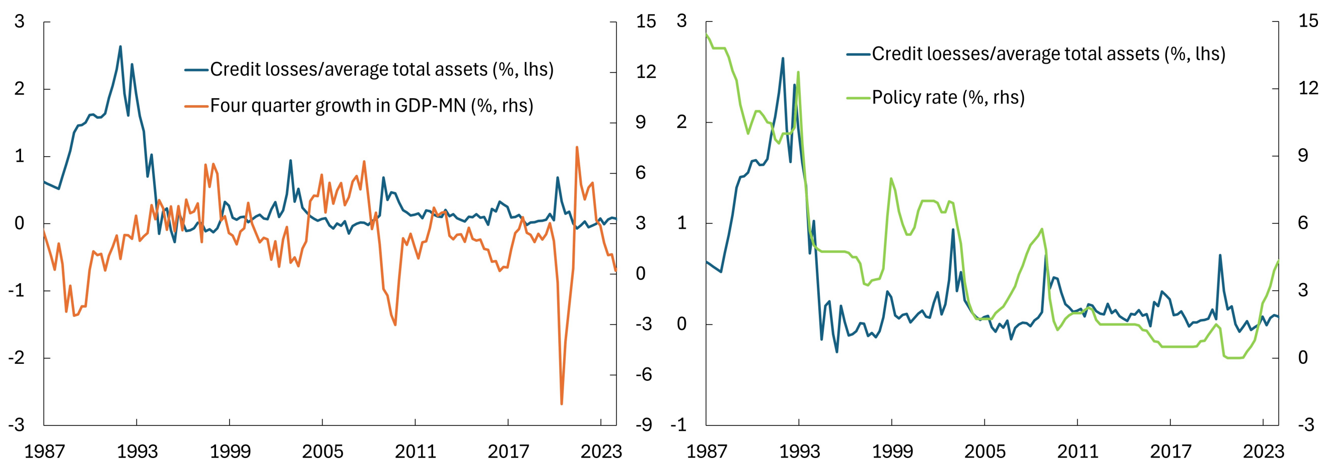
Since our focus is on the development of the aggregate banking sector over time, the empirical literature on the cross-section of banks is not covered in this review. Furthermore, competition among banks may conceivably impact banks' risk taking and credit losses. We do not cover the potential impact of bank competition in this Memo.

3.1 The effects of macro economic activity

In the literature, positive income developments are associated with a decrease in credit losses relative to ATA. This aligns with expectations, as higher earnings across firms and more stable incomes for households enhance their capacity to service debt. In Norway, credit losses are negatively correlated with Norway's mainland GDP[9] (GDP-MN) growth (Chart 4a), with the severity of losses varying across recessions. For example, during the Norwegian banking crisis of the late 80s/early 90s, credit losses increased heavily compared to the drop in economic activity.

Chart 4: *Credit losses and macroeconomic variables*

(a) *Credit losses* and GDP-MN growth* (b) *Credit losses* and the policy rate*



**Annualised and break-adjusted time series for the sum of seven large Norwegian banks. Banks' credit losses are reported with a positive sign.*
Sources: S&P Capital IQ, Statistics Norway and Norges Bank

Similarly, Albertazzi and Gambacorta (2009) look at credit losses among international banks and find a historical negative correlation with GDP in the period prior to the financial crisis.[10] They interpret the results as showing that negative macroeconomic conditions deteriorate banks' credit portfolio quality. Studies on credit losses, such as Altavilla et al. (2018) and Buncic et al. (2019), show a negative correlation between economic activity and credit losses in the EU and Sweden, respectively. For Norway, Hjelseth et al. (2022) find that a decrease in GDP-MN growth increases bankruptcy debt rates, while Berge and Boye (2007) identify a significant positive relationship

[9] GDP is usually the most relevant and easily available measure of both economic activity and income

[10] Albertazzi and Gambacorta (2009) appear to estimate the effect on credit losses that is not normalised by dividing by total assets.

between the unemployment rate and the aggregate default rate in both the corporate and household sectors. However, to account for the sharp and variable spikes in credit losses, these studies also incorporate complementary factors, such as asset prices, commodity prices, expectations, and/or interest rates.

Some studies focus instead on the nonlinear relationship between credit risk and different measures of economic activity. In a crisis, historical relationships can break down and lead to a marked decline in borrowers' ability and willingness to service their debts. Hardy and Schmieder (2013), Hardy and Schmieder (2020) and Ong et al. (2023) study the pattern of credit losses around various international crises and find that high credit losses are usually accompanied by sharp economic downturns. In addition, the behaviour of credit losses (and other banking variables) is highly nonlinear during crises. For stress testing purposes, they emphasise the importance of higher point-in-time credit loss correlations (with GDP) that reflect the economy-wide increase in risk during financial crises. Similarly, Laeven and Valencia (2018) present a database on systemic banking crises and show that the level of aggregate non-performing loans (reflecting the level of credit risk) varies considerably across banking crises.

Using an analytical rather than empirical approach, the finance literature highlights the inherent nonlinearity of credit losses in relation to economic conditions. For instance, Vasicek (2016) derives the credit loss probability distribution for a loan portfolio, emphasising that costs of credit loss are inherently nonlinear: as economic conditions deteriorate, there is significant upside risk of higher credit losses, whereas improved conditions offer no corresponding downside risk. Appendix A presents a simple example demonstrating how the credit loss ratio of a loan portfolio can exhibit nonlinear behaviour in response to a common factor, such as GDP growth or property prices.

3.2 The effects of interest rates

Lower interest rates may (in isolation) enhance borrowers' debt service capacity, which in turn can be expected to reduce credit losses. The extent to which changes in policy rates pass through to banks' corporate lending rates varies by country and industry, as noted in Kerola et al. (2024). In Norway, 95 percent of outstanding corporate loans are at floating rates (Cao et al. (2023)) indicating strong pass-through. Similarly, the share of bank lending to households at variable rates in Norway is also high, meaning policy rate changes directly influence borrowing conditions and debt servicing capacity.[11][12]

Lower interest rates can also improve borrowers' balance sheets by increasing asset values, thereby boosting collateral and reducing lenders' risk exposure (e.g., through lower LGDs). This

[11] In Norway, over 90 percent of mortgage loans are at variable rates, a far higher share than in most OECD countries, see figure 6 on page 16 in Hoenselaar et al. (2021).

[12] Norwegian banks provide credit and receive deposits largely at a floating nominal interest rate, which they can adjust after a notification period. In practice, these interest rates closely track the policy rate, and banks' corporate lending rates are often linked to a reference rate such as NIBOR.

"financial accelerator" mechanism (see Bernanke and Gertler (1995)) further suggests that lower interest rates should reduce credit losses relative to assets.

However, a low interest rate level may also increase banks' risk taking. Banks may 'search for yield' and issue riskier loans when policy rates and market rates are low.[13] Higher risk taking may pull in the direction of higher credit losses when interest rates are low, possibly with a delay. Karapetyan (2016) finds that Norwegian banks that are less capitalised lend more to ex-ante risky firms when money market rates are low than well capitalised banks. That is, less capitalised banks are exactly the banks expected to be most likely to increase risk-taking due to limited liability and moral hazard.

Several empirical studies instead consider the net effect of lower interest rates on banks' credit losses. A key finding is that lower (higher) interest rates appear to reduce (increase) credit losses relative to assets.[14]

Both Altavilla et al. (2018) and Borio et al. (2017) apply panel regressions to estimate the effects of interest rates on credit losses. Studying banks in the euro area and a wider set of countries, respectively, they both find that a higher short-term interest rate leads to higher credit losses, controlled for a set of macroeconomic, bank and financial variables. Borio et al. (2017) find that the relationship between interest rate changes and losses is nonlinear, with interest rate increases having a stronger effect on credit losses when the interest rate is initially at a low level. They suggest that borrowers' balance sheets may be in worse shape when the interest rate is increased from a very low level, because a low rate often coincides with a deep recession.

In Windsor et al. (2023), a panel-regression for banks in 10 countries is conducted (separately for each country). Overall, the authors find that lower interest rates reduce credit losses as a share of total assets. They conclude that the decreased debt-servicing burden resulting from lower rates is sufficient to offset the possible increase in bank risk-taking. In particular, they point out that lower interest rates reduce the interest burden for all borrowers with variable-rate loans, whereas the increased risk-taking primarily impacts the flow of new loans. As a result, lower interest rates are generally expected to reduce loan loss provisions.

Chart 4b illustrates that in Norway, peak credit losses have usually occurred during periods when the policy rate was sharply reduced to stabilise the economy. An exception to this is the Norwegian banking crisis, where the policy rate was gradually lowered from exceptionally high levels, primarily driven by the fixed exchange rate regime in place at the time. Table B.2 shows

[13] Higher risk-taking may be banks' way of compensating for otherwise lower net interest income, as their net interest rate income typically falls when policy rates are low see e.g. Alstadheim and Johansen (2023). Windsor et al. (2023) summarise the literature on risk-taking and mention three channels: Sticky return targets in combination with lower profits when interest rates are low, falling risk perceptions when income and asset values are higher, and lower risk premia with forward guidance by central banks in a low-interest rate environment.

[14] These international studies primarily examine loan loss provisions reported in the income statement, which are closely aligned with our measure of credit losses. For our purposes, the distinction between the two is negligible. However, it is important to distinguish between loan loss provisions in the income statement and those on the balance sheet (discussed in Section 2), as the latter represent a stock measure rather than a flow.

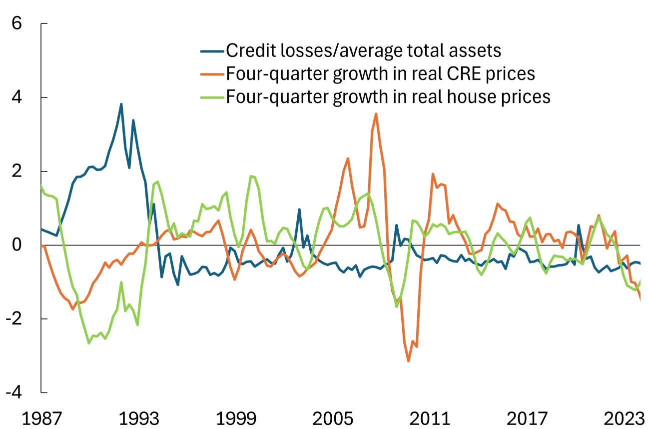
that the policy rate is relatively robust as a predictor of credit losses in Norwegian data.

3.3 The effects of property prices

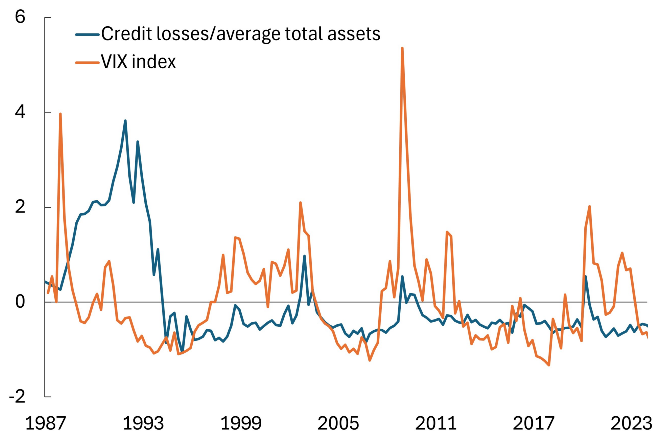
Property prices, including residential and commercial real estate (CRE), play a critical role in the financial system. They directly impact loan collateral values (affecting LGDs) by determining the value of the assets securing loans, while also influencing the willingness and ability of firms and households to service their debt (affecting PDs). In Norway, significant increases in credit losses were only observed during periods of large and simultaneous declines in CRE prices and residential house prices (Chart 5a).

Chart 5: *Credit losses and financial indicators*

(a) *Credit losses* and property prices*



(b) *Credit losses* and VIX index*



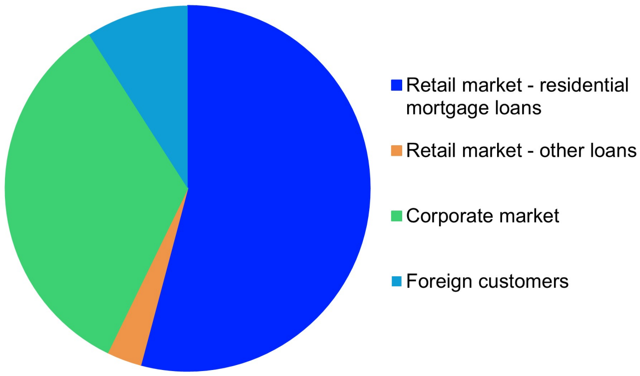
**Annualised and break-adjusted time series for the sum of seven large Norwegian banks. Banks' credit losses are reported with a positive sign.*
All variables are standardised by subtracting the average and dividing by the standard deviation.
Sources: CBRE, DN, Eiendom Norge, Finn.no, FRED, JLL, OPAK, Real Estate Norway, S&P Capital IQ, Statistics Norway and Norges Bank

Historically, credit losses on CRE exposures have been a major driver of bank losses during international financial crises (Kragh-Sørensen and Solheim (2014)). In Norway, recent concerns are twofold: First, CRE lending accounts for nearly half of large Norwegian banks' commercial lending (Bjørland et al. (2022); see Chart 6b). Second, the CRE sector has higher debt levels relative to income than other sectors, making it particularly vulnerable to rising interest rates and challenges in loan refinancing (Bjørland, 2023).

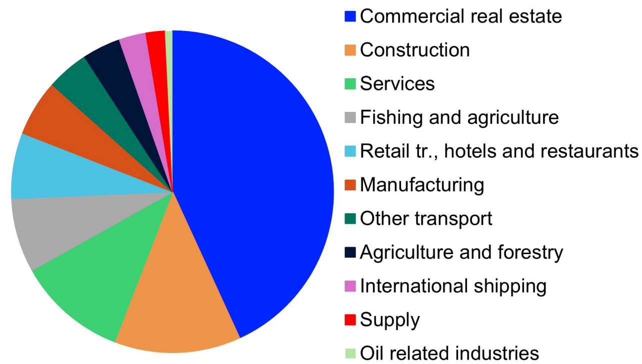
Residential mortgages make up more than 50 percent of large Norwegian banks' total lending to customers (Chart 6a). Although losses within this sector are typically low relative to lending volumes, even small increases can contribute significantly to total credit losses. However, loss rates on residential mortgages are generally lower than on corporate loans. One contributing factor is the full-recourse structure of Norwegian mortgage loans (Kragh-Sørensen and Solheim (2014)) and Aarland and Santiago (2023)).

Chart 6: *Distribution of large Norwegian banks' credit exposure*

(a) *All customers*



(b) *Corporate customers*



Seven large Norwegian banks and wholly-owned mortgage companies. 2023.
Sources: Statistics Norway and Norges Bank

Although direct links between bank losses and housing prices are difficult to establish, there are notable indirect effects through changes in household consumption. Studies using UK data (Campbell and Cocco (2007); Disney et al. (2010)) and US data (e.g., Aladangady (2017)) have analysed the relationship between house price changes and consumption. Campbell and Cocco (2007) find a stronger consumption effect compared to Disney et al. (2010) as they account for other macroeconomic factors impacting housing prices. Similarly, Aladangady (2017) identifies significant effects in the US, particularly for households with high debt-to-income ratios – a relevant finding given Norway's own elevated debt-to-income ratio. Furthermore, Disney et al. (2010) highlight asymmetric behaviour, wherein consumption decreases more sharply when house prices fall than it increases when house prices rise.

3.4 The effects of commodity prices

Several commodity prices are key cyclical indicators for the Norwegian economy. In addition, they directly influence income (and debt-servicing capacity) in several industries such as fishing, agriculture and forestry, manufacturing and oil-related industries (Chart 6b). For Norway, Hjelseth et al. (2022) find that decreasing salmon prices significantly increase the probability of bankruptcy in fishing and fish farming.

Given the significant role of the petroleum sector in the Norwegian economy, oil prices have a profound influence on the economic cycle and the profitability of firms in Norway. Grippa and Mann (2020) use an SVAR model to explore the interaction between the oil sector and the broader Norwegian economy during the period 2010-2019. Despite the limited direct exposure of most Norwegian banks to the oil sector, their analysis indicates that declines in oil sector revenue lead to a statistically significant rise in Norwegian banks' credit losses.

3.5 The effects of uncertainty and other conditions

Banks' credit losses can be affected by many other conditions such as uncertainty, expectations regarding the economic outlook, better credit management, and new emerging risks.

Altavilla et al. (2018) document that a higher VIX index is associated with higher credit losses. At the same time, the nonlinearity of credit losses in relation to economic conditions (see Appendix A) suggests that higher volatility in economic conditions, should in theory increase expected credit losses. Intuitively, when the economy alternates between a severe downturn, characterised by high credit losses, and a strong upswing with negligible losses, average losses remain elevated. This is illustrated in Chart A.2 in Appendix A, which highlights the nonlinearity of credit losses as a function of economic conditions. In contrast, a consistently stable and moderately positive economic state results in relatively low expected credit losses. Consequently, greater volatility in income levels is typically associated with somewhat higher expected losses. We notably observe that Norwegian banks' credit losses are positively correlated with the VIX index (Chart 5b). Empirically, Tran and Houston (2021) document that discretionary loan loss provisions (distinguishing between normal and discretionary provisions) increase with higher economic policy uncertainty. They argue that economic policy uncertainty provides 'cover' for managers' decisions to increase loan loss provisions.

Expectations about the economic outlook also play an important role in shaping the impact of macroeconomic developments on bank profitability (see, e.g., Altavilla et al. (2018)). Under IFRS 9, such expectations are explicitly incorporated into the calculation of expected losses when banks assess credit losses over the lifetime of loans (see Section 2).[15] However, as Grünberger (2012)'s model-based analysis suggests, the cyclicality of impairment recognition under IFRS 9 depends on banks' ability to anticipate changes in the economic outlook.

Better credit management typically results in improved credit quality in banks' loans, and credit losses as a share of ATA can be expected to be both lower and less volatile. Risk weights, which are intended to reflect banks' exposure to losses, have declined for large banks since the introduction of the capital adequacy framework (Basel II) in Norway in 2007 (Andersen and Winje (2017)). In addition, banks have gradually shifted their exposure towards the retail market, which is associated with lower risk weights and lower losses during international crises (Kragh-Sørensen and Solheim (2014)). In a previous parallel top-down and bottom-up solvency stress test, larger Norwegian banks cited improved risk management as a key reason to expect lower credit losses than Norges Bank expected (Havro et al. (2011)). IMF (2015) showed similar results in a parallel stress test and pointed to less conservative risk parameters and survivorship bias to explain the lower credit losses in the bottom-up exercise. However, to accurately quantify credit risk – especially its development over time – remains challenging (Andersen and Winje (2017)).

[15] Banks are required to model expected losses for the lifetime of loans classified in stages two and three, i.e., those with elevated credit risk.

As a result, it is particularly difficult to determine the historical impact of risk management on credit losses.

Looking ahead, emerging risks, such as those related to climate change, are likely to become increasingly prominent. Stricter requirements for climate transition can be expected in the years ahead and Norwegian banks are exposed to industries that will have to implement substantial climate-related changes.[16] Hjelseth et al. (2024) show that several industries can experience large cost increases. However, these individual industries only account for a limited proportion of banks' corporate lending in Norway. Grippa and Mann (2020) study three possible transmission channels for transition risk shocks to the Norwegian financial system and find that a sharp increase in carbon prices would have a significant but manageable impact on banks.

4 Econometric model: Linear and nonlinear version

To examine the relationship between credit losses and the real economy, we first estimate a standard, linear VAR model for the Norwegian economy using quarterly data from 1992Q4 to 2023Q4. This baseline model includes the following variables: the four-quarter growth rate of real GDP-MN, the CPI-ATE inflation rate (four-quarter growth rate of consumer price index adjusted for tax changes and excluding energy products), the level of the policy rate, the level of the real exchange rate based on I44[17], and annualised credit losses in percent of ATA.[18] These variables constitute the vector y_t of endogenous variables in the equation below.

In subsequent steps, the baseline model is extended to include the Norwegian banking crisis, the financial drivers and other relevant variables discussed in Section 3, and a nonlinear framework using quantile regressions. To isolate the effects of each step, we estimate multiple extensions of the baseline model.

We estimate the VAR with four lags of the dependent variables y_t, covering one year of quarterly data. Several criteria – including the Akaike Information Criterion, the sequential modified LR test, and the final prediction error – suggest five lags, while the Bayesian Information Criterion points to one, see Appendix C.[19] Since the linear framework yields very similar impulse responses at both four and five lags, we report results based on four lags in Section 6.[20] This choice reflects

[16] Johansen and Solheim (2023) conducted a qualitative survey and found that large Norwegian banks are increasingly integrating climate-related risks into their risk management processes. Most banks aim to support clients' transition efforts, meaning that climate-related risks remain on the banks' balance sheets in the short term.

[17] Although there is limited literature to support a direct relationship between the real exchange rate and credit losses, it is incorporated into the model to strengthen the interactions among the macroeconomic variables.

[18] The included data are expressed as levels in the model, but GDP-MN and CPI-ATE are included as logarithmic differences over the past four quarters.

[19] The relatively large number of lags reflects the delayed effects of economic activity on banks' growth and earnings. Andersen (2020) and Alstadheim and Johansen (2023) also show that well-specified models of banks' expenses and net interest income in Norway require lag lengths spanning one to two years.

[20] At five lags, the null of zero autocorrelation is strongly supported, with ample margin. At four lags, the diagnostics suggest some autocorrelation, but this does not materially affect the impulse responses.

the midpoint between the AIC and BIC recommendations, while also being more parsimonious and consistent with the nonlinear framework, where computational constraints necessitate fewer lags.

We then identify five different shocks using a Cholesky decomposition (with the ordering of variables as they are listed above) of the estimated reduced-form variance covariance matrix.

In order to investigate potential nonlinear effects of shocks on the *distribution* of losses (as opposed to the effect on the central expectations of losses as captured by the VAR), we follow Forni et al. (2024) and combine the VAR-estimation with quantile regressions. We use their approach to estimate the quantiles of our variable of interest (credit losses in percent of ATA) using conditional quantile regressions.[21] Let x_t be the target variable (credit losses in our framework) whose distribution has to be predicted and let y_t be the vector of n macroeconomic variables included in the VAR above. Let $w_t = Wy_t$ be the r-dimensional subvector of variables which are important to forecast x_t, where W is a $r \times n$ matrix of zeros and ones selecting the appropriate predictors in y_t. In what follows, W is an identity matrix, such that $w_t = y_t$. The variables included in the conditional quantile regression are thus the same as the VAR for the Norwegian economy.

The quantiles of the h-period ahead forecast distribution of x_t are estimated using conditional quantile regressions. The τ-th quantile, Q_t^τ, of x_{t+h}, conditional on the predictors w_t, is a linear function of the predictors:

$$Q_t^\tau = \beta_\tau'(L)w_t = \beta_\tau'(L)Wy_t = \tilde{\beta}_\tau'(L)y_t,$$

where $\tilde{\beta}_\tau'(L) = \beta_\tau'(L)W$ and $\beta_\tau(L)$ is a r-dimensional vector of polynomials in the lag operator L. Since the quantiles are linear in y_t, any linear combination z_t^j of the quantiles can be written as a linear combination of current and lagged macroeconomic variables:

$$z_t^j = \gamma_j'(L)y_t, \tag{1}$$

where $\gamma_j(L) = \gamma_{j0} + \gamma_{j1}L + ...\gamma_{jq}L^q$ is an n-dimensional vector of polynomials in L.

The parameters $\beta_\tau(L)$ are estimated using the smoothed quantile regression estimator recently proposed by Fernandes et al. (2021) and Natal and Horta (2022). Estimates of the polynomials $\gamma_j(L)$ can simply be obtained by replacing the quantile parameters $\tilde{\beta}_\tau(L)$ with their estimates obtained from the quantile regression. Any linear combination of the quantiles, $z_t^j = \gamma_j'(L)y_t$, has the following dynamic structural representation:

$$z_t^j = \gamma_j'(L)B(L)u_t, \tag{2}$$

[21]For an illustrative example highlighting the importance of this flexible approach, refer to the discussion at the start of Section 6.2.

where the polynomial $\gamma_j'(L)B(L)$ represents the impulse response functions to the structural shocks u_t.

We focus on four measures of the distribution of credit losses: the 95th percentile, upside risk, uncertainty and skewness. *Upside risk* is a measure of the right tail and is defined as the distance of the median from the 95th percentile:

$$z_t^D = \gamma_L'(L)y_t = Q_t^{0.95} - Q_t^{0.5} = \left[\beta_{0.95}'(L) - \beta_{0.5}'(L)\right] B(L)u_t,$$

Uncertainty is defined as the difference between the 95th and 5th percentiles:

$$z_t^V = \gamma_U'(L)y_t = z_t^U + z_t^D = [\beta_{0.95}'(L) - \beta_{0.05}'(L)]B(L)u_t.$$

Skewness is measured as the non-normalised Kelley skewness Kelley (1947), which is the sum of the 5th and 95th percentiles minus twice the median:

$$z_t^A = \gamma_A'(L)y_t = z_t^U - z_t^D = [\beta_{0.95}'(L) + \beta_{0.05}'(L) - 2\beta_{0.5}'(L)]B(L)u_t.$$

We focus on the 95th and 5th percentiles when measuring risk, uncertainty and skewness as stress testing is concerned with understanding extreme, yet still plausible, outcomes – that is, the tails of the distribution that pose the greatest risk to credit resilience.

5 Data

Our linear core model estimates are based on data from 1992Q4 to 2023Q4. To account for a severe crisis, we expand the sample to include the banking crisis of the late 80s/early 90s. Properties of the main time series are documented in Appendix B.

Banks' credit loss data[22] are obtained from ORBOF bank statistics[23], S&P Capital IQ and OECD banking statistics. The time series for the seven large Norwegian banks are aggregated to one time series. This time series is adjusted for institutional conditions such as mergers and transfers of loans to covered bond mortgage companies.[24] The aim is for all institutions included in the current aggregate of the seven large banks to also be included back in time to allow the focus to be on the interaction between the macroeconomy and the aggregate of the large banks

[22] We aim to document the cyclicality of all income statement items (see for example Chart 1 and Alstadheim and Johansen (2023)), and therefore rely on data with a slightly broader definition than credit losses. Specifically, we use S&P's time series for "impairments on financial instruments" and ORBOF's series for "losses on loans, guarantees, and securities". In both cases, credit losses are the predominant component driving the trends and volatility, which is sufficient for our analysis. Additionally, our aggregate time series has been adjusted for data breaks, as it spans over 40 years, a period during which definitions vary across time and data sources.

[23] Banks' and financial undertakings' financial reporting to the Norwegian authorities (ORBOF).

[24] For more background information and how transfers of loans to covered bond mortgage companies affect banks' balance sheets, see Bakke et al. (2010).

over time. It is particularly important to include banks that have merged into other banks due to poor performance when analysing the development of credit losses in order to account for potential survivorship bias. Quarterly figures in the period 1981-1992 have been estimated using a linear interpolation of annual figures from ORBOF and OECD. The percentage point change in credit losses, expressed as a percent of ATA, is based on time series covering all banks from OECD banking statistics in the period 1981-1986. The dataset for banks' financial statements is described in more detail in Appendix A in Alstadheim and Johansen (2023) for the period 1987 to 2023.[25] Banks' credit losses are normalised, as we measure them as a percentage of ATA. This benchmark (as opposed to, e.g., credit losses relative to total gross lending) is chosen in order to make different items in banks' income and cost account comparable; see also footnote 22.

Macro indicators such as GDP-MN, CPI-ATE, the policy rate and the real exchange rate are obtained from Statistics Norway and Norges Bank. In spring 1993, Norges Bank's liquidity management system was restructured, and from June 1993, the policy rate changed from the overnight lending rate (D-loan rate) to the sight deposit rate. The observation used for the policy rate in 1993 Q2 is a weighted average of the D-loan rate and the sight deposit rate in the quarter.[26] From 1988 until 1993Q1, the D-loan rate represents the policy rate, and for the period 1980-1988, we use the CB-Loan marginal, see Norges Bank (2025).

In addition to the core variables, we incorporate a range of model variations that include property prices, the oil price, the VIX index, an indicator of households' expectations of the economy one year ahead, the household interest rate burden and alternative measures of economic activity. For further details, see Appendices D and E.

6 Results

First, we examine the responses of credit losses to the identified shocks to the macroeconomic variables within the linear version of our VAR model. Second, we expand our starting-point model to cover the Norwegian banking crisis and incorporate a range of additional variables into the estimation. Third, we relax the linear constraints of the baseline model by adopting a more flexible approach using quantile regressions. By estimating the distribution of credit losses relative to ATA, we can distinguish between the expected effect of macro shocks on credit loss peaks and median credit losses.

[25] Several historical regulatory changes may have influenced the interaction between the macroeconomy and credit losses. For example, the impact of different accounting standards on credit losses, as discussed in Section 2, provides insight into such effects. Such regulatory changes that have not been corrected may add some noise to our results.

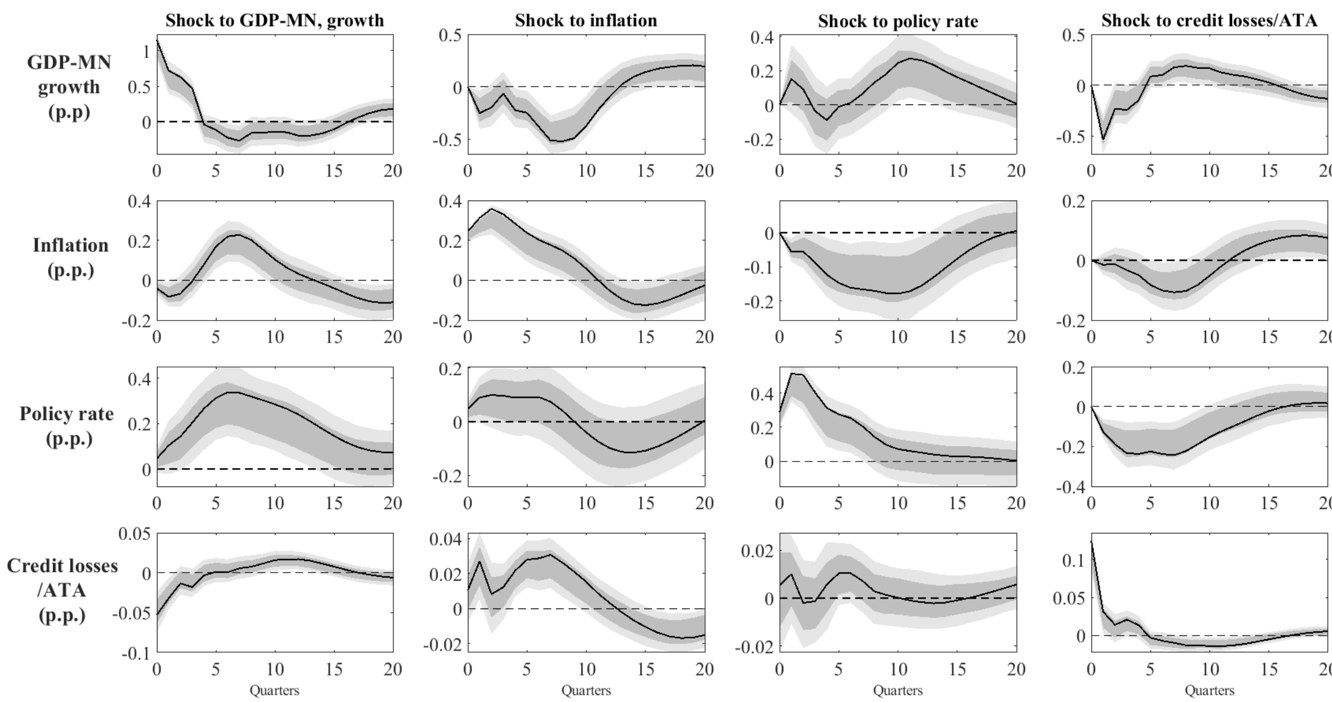
[26] This is consistent with Norges Bank's overview of Changes in the policy rate.

6.1 The linear VAR-model

Applying the linear framework and the Cholesky decomposition presented in Section 4, we find that macroeconomic shocks have a significant effect on credit losses (see bottom row in Chart 7).[27]

We find that a positive (or negative) one-standard-deviation shock to GDP-MN growth, shown in the first column of Chart 7, results in a 0.05 percentage-point decline (or increase) in annualised credit losses in percent of ATA (bottom row, first column). The response is immediate and reverts to zero at the same pace as GDP-MN growth (first row, first column). The shock can be interpreted as a positive demand shock as inflation, GDP-MN growth and the policy rate all increase. Even though the policy rate increases (third row, first column), presumably increasing firms and households' debt service costs, the model implies that the improved economic conditions will dominate and lower credit losses as a share of ATA.

Chart 7: *Shocks to macro economic variables - Norwegian banking crisis excluded*



The impulse responses of GDP-MN growth, inflation, the policy rate and credit losses to a one-standard-deviation increase in the respective shocks. The shaded areas are 90% and 68% confidence bands. Banks' credit losses are reported with a positive sign. The estimation period is 1992Q4-2023Q4.
Source: Norges Bank

A one-standard-deviation positive shock to inflation, shown in the second column of Chart 7, leads to an increase in credit losses as a percentage of ATA (bottom row, second column). This effect is more muted but longer lasting compared to the response following a GDP-MN growth shock. The prolonged impact on credit losses may be attributed to a sustained negative response

[27] The shock to the real exchange rate is highly muted and statistically insignificant for credit losses. As a result, it is not shown in the Charts but it is still included in the model to enhance its overall dynamics.

in GDP-MN growth (first row, second column). The inflation shock resembles a negative supply shock: GDP-MN growth declines, while inflation and the policy rate rise. Our findings suggest that, over the time horizon considered, the combined effect of reduced economic activity and higher interest expenses outweighs the potential mitigating impact of inflation in reducing the real debt burden of households and firms.

For a policy-rate shock (third column of Chart 7), credit losses relative to ATA increase somewhat (bottom row, third column), even though economic conditions otherwise remain relatively unchanged (top row, third column). Although a higher policy rate may reduce risk-taking, the model suggests that increased debt service costs outweigh this effect (see discussion in Section 3.2), leading to higher credit losses as a percentage of ATA; however, this estimated increase is not statistically significant. Our findings are consistent with those of Altavilla et al. (2018), who, using a similar linear framework for the euro area, identified a positive effect of monetary easing on credit quality. Like us, they find that the positive effects of a rate cut more than offset the credit-quality deterioration caused by increased risk-taking.[28]

To our knowledge, no directly comparable studies specifically investigate the impact of shocks to GDP-MN growth or inflation on credit losses in percent of ATA. However, the linear VAR model identifies a negative correlation between GDP-MN growth and credit losses in percent of ATA (irrespective of shocks), which aligns with the findings reported in the existing literature (see Section 3.1).

As documented in Appendix D, these results are robust to a large number of model variations. The inclusion of other potential explanatory variables, such as property prices, the oil price, expectations or a risk indicator in the model, does not change these main results. In addition, simple proxies for banking-sector riskiness leave the key impulse responses largely unchanged. Alternative credit loss measures – normalised by gross lending or expanded to all banks and mortgage companies – likewise do not materially alter the key responses after adjusting for level and volatility.

Even though our results are in line with the (linear) literature, we note that the responses to macroeconomic innovations are fairly small: a negative one-standard-deviation shock to GDP-MN growth (which amounts to a 1 percentage point decrease in the growth rate) increases credit losses to ATA by only 0.05 percentage point (bottom row, first column in Chart 7), corresponding to just 1/6 of the standard deviation of the time series. In isolation, a 0.05 percentage point higher annual credit loss as a percentage of ATA roughly corresponds to a 0.5 percentage point reduction in the return on equity for the large Norwegian banks. Moreover, a variance decomposition reveals that approximately 50 percent of the variation in credit losses can be attributed to shocks in the selected macroeconomic variables, with the remainder left unexplained (Appendix E). This result closely aligns with the findings of Hoggarth et al. (2005), who used a linear VAR model to estimate

[28]The response in Altavilla et al. (2018) is considerably more delayed compared to ours. This may be related to the nature of their monetary policy shock, which involves a flattening of the yield curve that fades gradually over time. In addition, their response is possibly linked to the feedback from improved economic outlook.

the relationship between write-off rates and the macroeconomy in the UK, with the primary explanatory power in the model attributed to the write-offs themselves. While macroeconomic factors explain a large share of the variation in credit losses, a historical shock decomposition (Chart F.1a in Appendix F) reveals that past spikes in credit losses are largely driven by shocks to credit losses themselves.

6.1.1 Including the Norwegian banking crisis and more financial variables

A potential reason for the muted response in credit losses to macroeconomic conditions could be the lack of a severe banking crisis in our sample. In Chart 8, we expand the sample to include the Norwegian banking crisis of the late 80s/early 90s. In contrast to other studies of credit losses in Norway that include the banking crisis, we extend the time series to include the pre-crisis period back to 1981Q4.[29][30] This longer horizon enables the full dynamics of the variables both in the run-up to the crisis and during its unfolding to be captured.

Many of the results discussed above remain robust when the estimation period is extended (compare Charts 7 and 8). However, the impact of a GDP-MN growth shock on credit losses becomes more prolonged (bottom row, first column in Chart 8), with credit losses returning to zero at a slower rate than GDP-MN growth. Furthermore, while the response of credit losses to a policy rate shock is significant in the extended sample (bottom row, third column in Chart 8), economic conditions deteriorate as the policy rate increases (top row, third column in Chart 8).

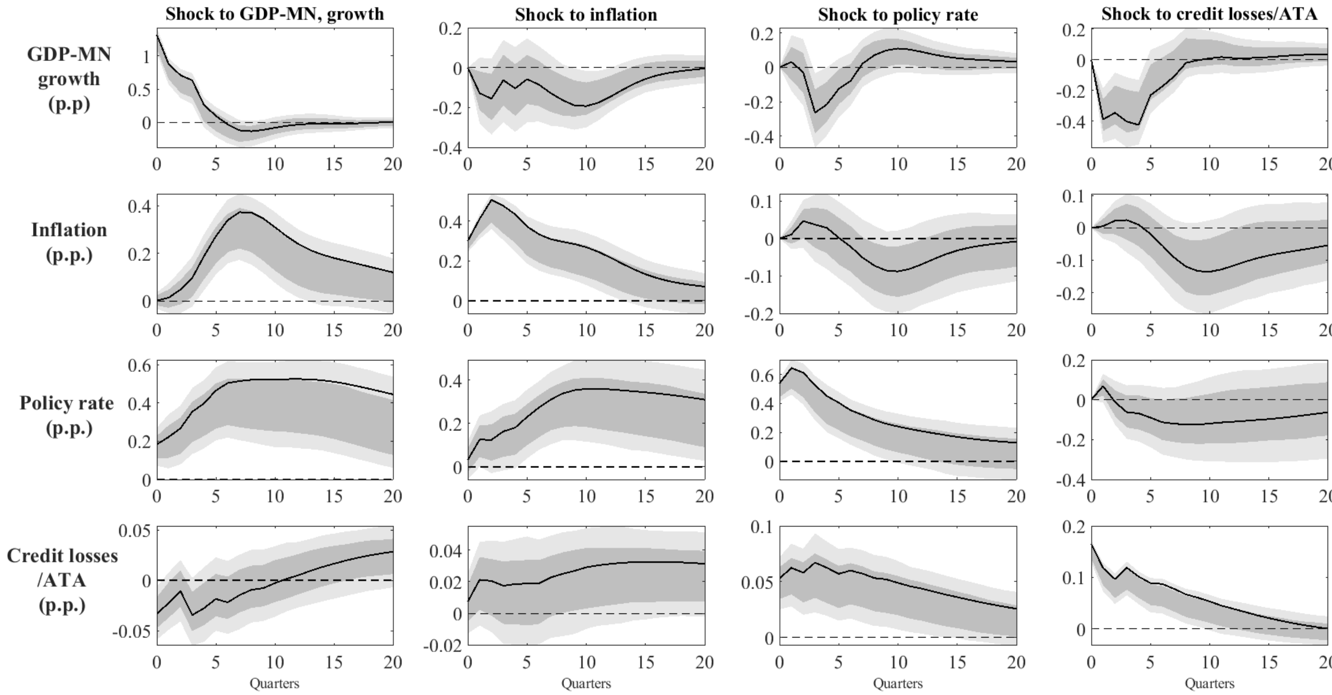
Even though the Norwegian banking crisis is included, the responses from the macroeconomic shocks to credit losses remain moderate and the variation and spikes are largely driven by shocks to credit losses themselves (Chart F.1b in Appendix F). The peak response to the interest rate shock, measuring 0.07 percentage point, is equivalent to just 1/8 of the standard deviation of the time series.[31]

[29]Most studies of the dynamics of credit losses and/or related variables for Norway start the sample at the onset of the crisis when credit losses had started to increase.

[30]Several sources suggest that credit losses were relatively stable during 1981–1986 (e.g., Chart 3.12 on page 97 in Johnsen et al. (1992) and Chart 14.10 on page 537 in Eitrheim et al. (2016)). Nonetheless, some uncertainty remains regarding the actual loss levels in Norwegian banks during the early 1980s, partly due to tax-driven practices where provisions were allocated to an *en bloc* fund – a collective reserve for loss provisions (Hoff (1989)). These practices significantly influenced the credit losses reported by OECD banking statistics in that period. Based on banks' annual reports, real credit losses – adjusted for bloc fund provisions – are estimated to be 10–30 basis points lower than those reported in OECD banking statistics as a percentage of ATA. However, these loss levels are mostly captured by the deterministic components of the VAR model, so persistent shifts do not significantly affect the model's dynamics. Robustness checks using alternative pre-crisis loss levels confirm stable results when extending the data back to 1981.

[31]When we include the Norwegian banking crisis in the sample the standard deviation of credit losses in percent of ATA increases from 0.31 to 0.56 percent, see Appendix B.

Chart 8: *Shocks to macroeconomic variables - Norwegian banking crisis included*



The impulse responses of GDP-MN growth, inflation, the policy rate and credit losses to a one-standard-deviation increase of the respective shocks. The shaded areas are 90 % and 68 % confidence bands. Banks' credit losses are reported with a positive sign. The estimation period is 1981Q4-2023Q4.
Source: Norges Bank

Next, we expand our VAR framework by incorporating a broad range of additional variables to address potential omitted factors that might explain credit loss spikes. The additional variables are motivated by the literature review in Section 3. To assess the impact of each model expansion, we estimate a variety of models, including two models that incorporate a mix of these additional variables.

Appendix E presents the variance decomposition of the models. The results show that even with the inclusion of additional variables – such as property prices, the oil price, expectations, alternative interest rates or a risk indicator – most models attribute only about half of the variation in credit losses to other variables than credit losses. Notably, the FAVAR[32] model (which captures common components from all added variables), assigns a larger share of the variation to these factors and GDP-MN growth. However, while these richer frameworks provide better explanations for specific credit loss spikes, they often perform worse across the rest of the sample and for other peaks.

[32]Factor-Augmented Vector Autoregression.

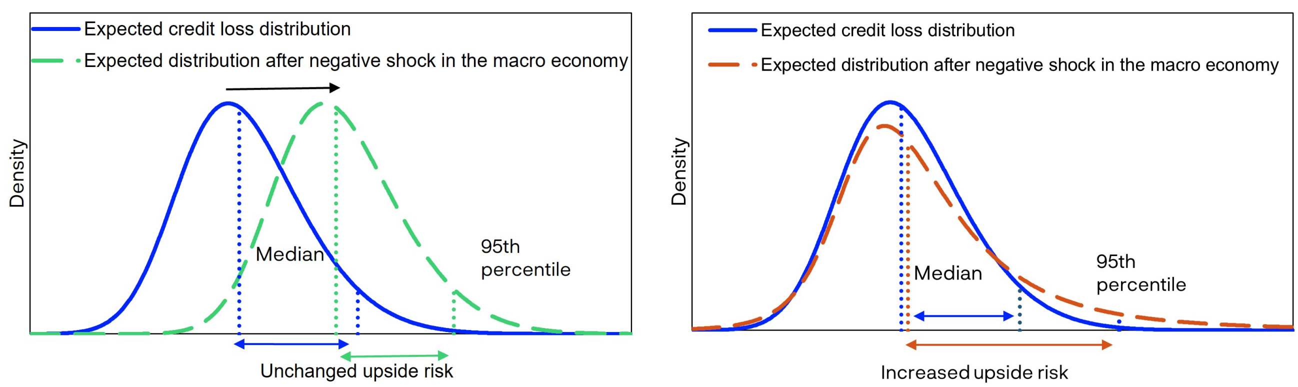
6.2 Nonlinear approach: Exploring the upside risk of credit losses

Rather than focusing on the expected mean of credit losses, we now shift our focus to the dynamics of the credit loss distribution by applying quantile regressions. Specifically, we analyse the response of the 95th percentile and the upside risk[33] (defined as the difference between the 95th percentile and the median) to shocks identified within the linear framework in Section 6.1.

Chart 9 illustrates the importance of relaxing the linear constraint and considering a more flexible approach that allows the study of the distribution of credit losses. By applying quantile regressions, we can distinguish between macro shocks that primarily affect the central expectations of credit losses, shifting the whole loss distribution (Chart 9a), and shocks that primarily affect the magnitude of credit loss peaks (Chart 9b). Only the latter example leads to an increased upside risk of credit losses.

Chart 9: *Illustration of how negative shocks to the macroeconomy can affect the upside risk of credit losses using credit loss distributions. In percent of ATA.*

(a) *Unchanged upside risk* (b) *Increased upside risk*



Source: Norges Bank

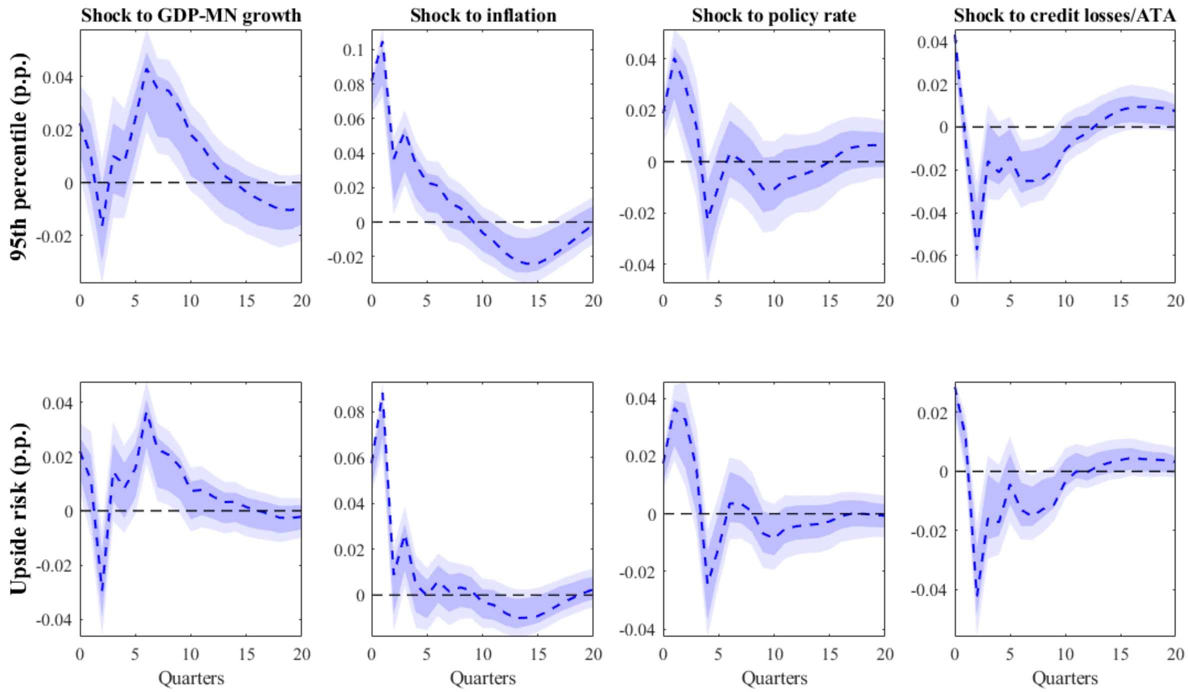
We study the impact on the 95th percentile and the upside risk of credit losses one year ahead and two quarters ahead. We assess a relatively short time horizon to be appropriate, as policymakers are primarily concerned with how current deteriorating economic conditions can influence the severity of potential credit loss spikes in the near term. This is particularly true in the context of stress testing, where the focus is on projecting the severity of an immediate tail event. Notably, these two time horizons (two quarters ahead and one year ahead) provide very different results for shocks to GDP-MN growth. Our analysis is presented with and without inclusion of the Norwegian banking crisis.

Chart 10 shows the estimated responses of the 95th percentile and upside risk one year ahead to the same shocks shown in Chart 7.[34] Notably, shocks to inflation and the policy rate have positive

[33]As banks' costs are reported with a positive sign, upside risk reflects the vulnerability to high credit losses. In contrast, if costs were reported with a negative sign, it would be the downside risk that indicates this vulnerability.

[34]The responses of the 95th percentile, upside risk, uncertainty and skewness *two quarters ahead* are reported in Appendix G.

Chart 10: *One-year-ahead responses of the 95th percentile and the upside risk of credit losses – Norwegian banking crisis excluded*

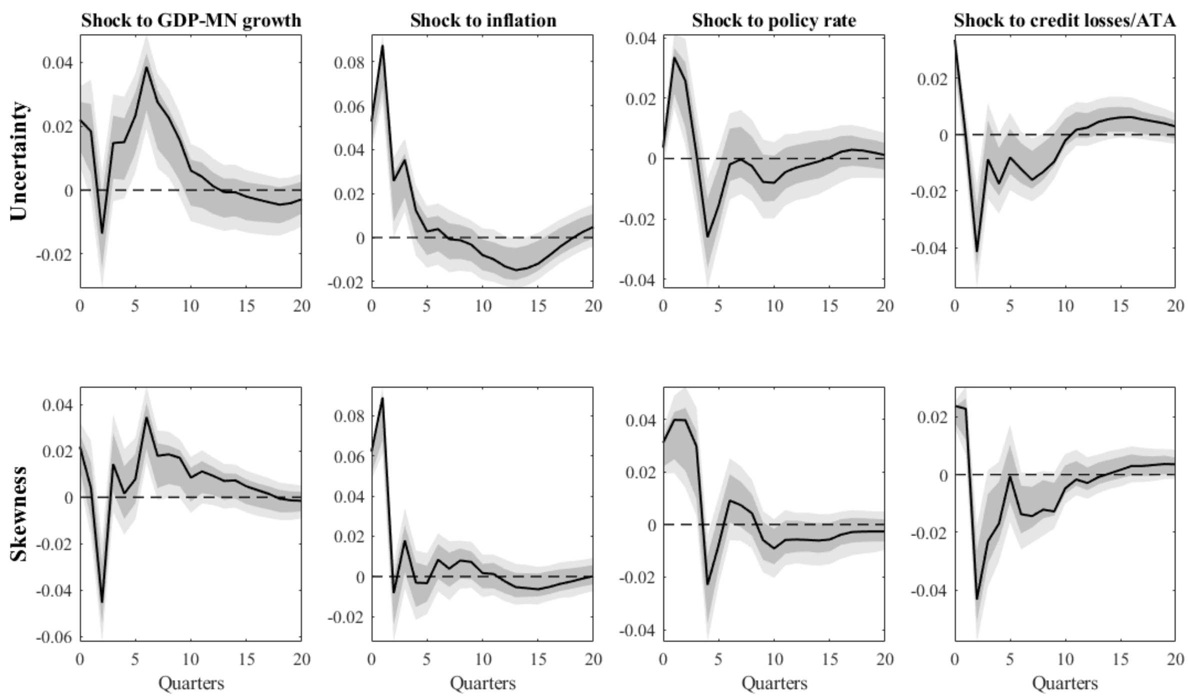


The impulse responses of the 95th percentile and upside risk of credit losses as a percentage of ATA, following a one-standard-deviation shock to the respective variables. Upside risk is defined as the difference between the 95th percentile and the median. The shaded regions represent the 90% and 68% confidence intervals, indicating the uncertainty around the estimated responses. Banks' credit losses are reported with a positive sign. The estimation period is 1992Q4-2023Q4.
Source: Norges Bank

and significant effects on the 95th percentile and the upside risk of credit losses (second and third column in Chart 10). This means that the upper tail of expected credit losses increases more than the median, consistent with the example shown in Chart 9b. While the effects of these shocks in the linear framework were more muted, the quantile regressions reveal a clear and significant impact on the upper tail of the credit loss distribution. Specifically, the responses for the tail are much larger in magnitude – particularly for inflation shocks. A one-standard-deviation increase in the inflation shock (second column in Chart 7) leads to a peak rise of 0.1 percentage point in the 95th percentile of credit losses (first row, second column in Chart 10). In contrast, the median response is much smaller, at about 0.01 percentage point. This is explicitly shown by subtracting the peak response in upside risk (second row, second column in Chart 10) from the 95th percentile response (first row, second column in Chart 10).

The shocks to GDP-MN growth and credit losses as a share of ATA are also significant for the 95th percentile; however, their effects are notably smaller in magnitude and shorter in duration (respectively, the first and last columns in the Chart 10). After a positive (negative) shock to GDP-MN growth, the estimation displays some increased (reduced) upside risk at around two years (bottom row, first column in Chart 10). This may reflect the reduced uncertainty associated with economic reversals and the tendency of banks to mitigate credit losses during periods of recovery following a downturn, see Section 2. Our linear analysis shows that the effects of a GDP-MN growth shock are quite immediate on credit losses relative to ATA (first column in Chart 7) and in the quantile regression we estimate the impact on the distribution one year ahead. In Chart G.2 in Appendix G we show that a shorter forecast horizon of two quarters, instead leads to reduced (increased) downside risk as a response to the positive (negative) GDP-MN growth shock.

Chart 11: *Responses of uncertainty and skewness – Norwegian banking crisis excluded*



The impulse responses of uncertainty and skewness of credit losses as a percentage of ATA, following a one-standard-deviation shock to the respective variables. Uncertainty is defined as the difference between the 95th and 5th percentiles. Skewness is the relative difference between the 95th percentile and the median compared to the median and the 5th percentile. The shaded regions represent the 90% and 68% confidence intervals, indicating the uncertainty around the estimated responses. Banks' credit losses are reported with a positive sign. The estimation period is 1992Q4-2023Q4.
Source: Norges Bank

The quantile VAR analysis reveals that only shocks to the policy rate and inflation result in a prolonged increase in the upside risk of the one-year-ahead distribution of credit losses. This can potentially be explained by the fact that the shocks to the policy rate and inflation combine higher interest burdens with stagnant or reduced economic activity (second and third column in Chart 7), thereby intensifying financial strain on firms and households. In contrast, negative GDP-MN growth shocks (see positive shock in first column in Chart 7) are accompanied by reduced interest expenses, which help alleviate financial strain. The heightened financial strain may explain the prolonged expectation of increased upside risk following shocks to inflation and the policy rate.

Chart 11 shows the impact of shocks on the entire estimated credit loss distribution, measured by uncertainty (the difference between the 95th and 5th percentiles) and skewness[35] (the relative difference between the 95th percentile and the median compared to the median and the 5th percentile). Following shocks to inflation and the policy rate (second and third column in Chart 11), both uncertainty and skewness increase, reflecting a widening of the right tail and highlighting that the 95th percentile is more reactive to financial strain (in line with the example shown in Chart 9b). This estimation effectively captures how expected credit losses, particularly potential credit loss peaks, rise in response to these shocks. In contrast, a positive (negative) shock to GDP-MN growth results in higher (lower) uncertainty approximately three years after the initial impact.

6.2.1 Including the Norwegian banking crisis

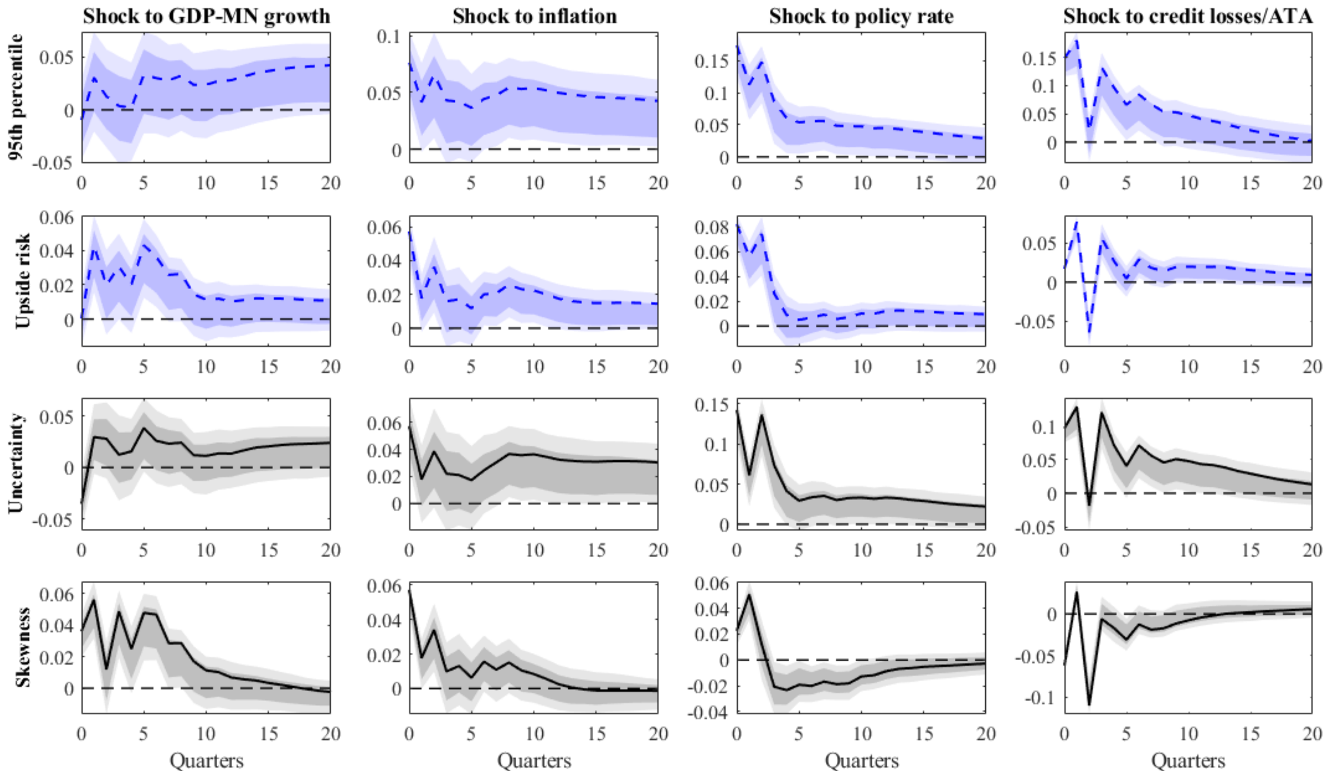
Lastly, we examine how the nonlinear results are affected by expanding the sample to include the Norwegian banking crisis. In line with our results in Chart 8, the responses in upside risk become more persistent and sizeable across all shocks (compare second row in Charts 10 and 12). The responses to shocks to inflation and the policy rate remain positive and significant (second row, second and third column in Chart 12).

However, the response in upside risk to a *positive* shock in GDP-MN growth is now both positive and significant, indicating that a negative shock to GDP-MN growth reduces the upside risk of credit losses (compare second row, first column of Charts 10 and 12). This finding can once again be rationalised through the lens of the linear VAR model (first column in Chart 8), where GDP-MN growth quickly reverts following the shock, while inflation and the mitigating policy rate response reach their peak approximately two years after the shock. The forecast horizon plays a critical role in the response to a GDP-MN growth shock. Specifically, a two quarter forecast horizon results in increased (decreased) upside risk directly following a negative (positive) shock to GDP-MN growth (see Chart G.2 in Appendix G).

Finally, the inclusion of the Norwegian banking crisis appears to shift the entire credit loss distribution in response to a credit loss shock (first and second row, fourth column in Chart 12). In addition, it widens the lower tail, as evidenced by increased uncertainty and a negative response in skewness (third and fourth row, fourth column in Chart 12).

[35] Skewness close to zero indicates a symmetrical distribution. Positive skewness reflects a longer right tail compared to the left, while negative skewness indicates a longer left tail compared to the right.

Chart 12: *One-year-ahead responses of the 95th percentile, upside risk, uncertainty and skewness – Norwegian banking crisis included*



The impulse responses of the 95th percentile, upside risk, uncertainty and skewness of credit losses as a percentage of ATA, following a one-standard-deviation shock to the respective variables. Upside risk is defined as the difference between the 95th percentile and the median. The shaded regions represent the 90% and 68% confidence intervals, indicating the uncertainty around the estimated responses. Banks' credit losses are reported with a positive sign. The estimation period is 1981Q4-2023Q4.
Source: Norges Bank

7 Policy exercises

This section presents two main policy exercises that build on the findings from Section 6.2. First, we investigate the historical drivers of upside risk through a shock decomposition, identifying the macroeconomic factors that have contributed to upside risk of credit losses over time. Second, we use quantile regression to establish data-driven benchmarks for credit losses within a stress-testing framework.

7.1 Historical shock decomposition of upside risk in credit losses

Chart 13 shows the historical expected distribution of credit losses two quarters and one year ahead, comparing the expectation for each quarter to the realised historical recognised credit losses[36].

Several key observations emerge:

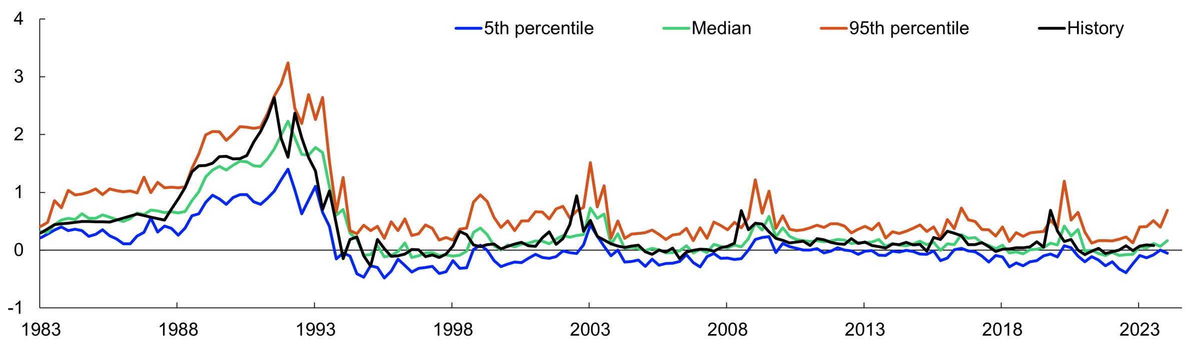
[36] Recognised credit losses refer to those reported in banks' income statements, as distinct from actual credit losses. See the discussion in Section 2.

1. Credit loss peaks are the observations that, by construction in the quantile regression, exceed the 95th percentile. These spikes emerge abruptly in the data, emphasising the importance of analysing this segment of the distribution.

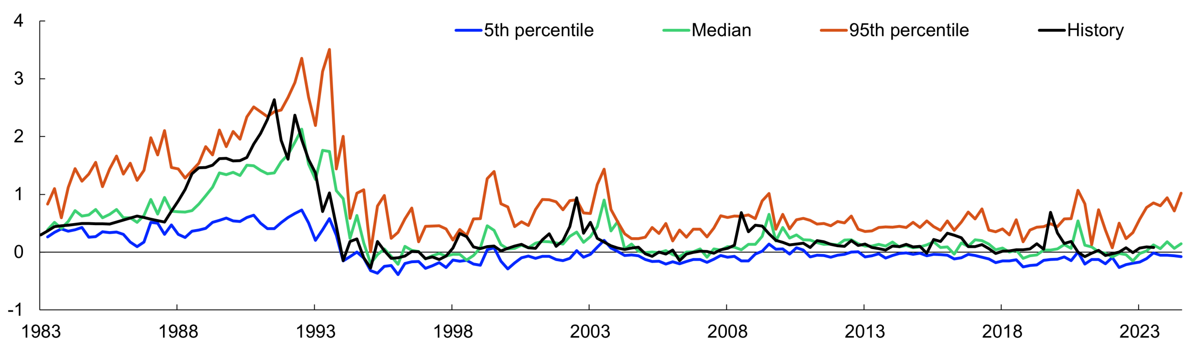
2. The one-year-ahead forecast is unsurprisingly[37] much wider than the two-quarters-ahead forecast and shows a noticeable skew towards higher credit losses, except during the Norwegian banking crisis.

3. The one-year-ahead distribution reveals significantly higher upside risk prior to the Norwegian banking crisis, along with somewhat higher upside risk ahead of the 2002-2003 spike and the global financial crisis. In contrast, the upside risk was relatively low in the lead up to the pandemic in 2020. Notably, consistent with this lower upside risk, the 2020 credit loss spike was comparatively modest[38] despite the substantial decline in GDP-MN growth during the pandemic (see Chart 4a in Section 3).

Chart 13: *In-sample prediction of credit loss distribution. Expressed as a percentage of ATA*



(a) *Two quarters ahead*



(b) *One year ahead*

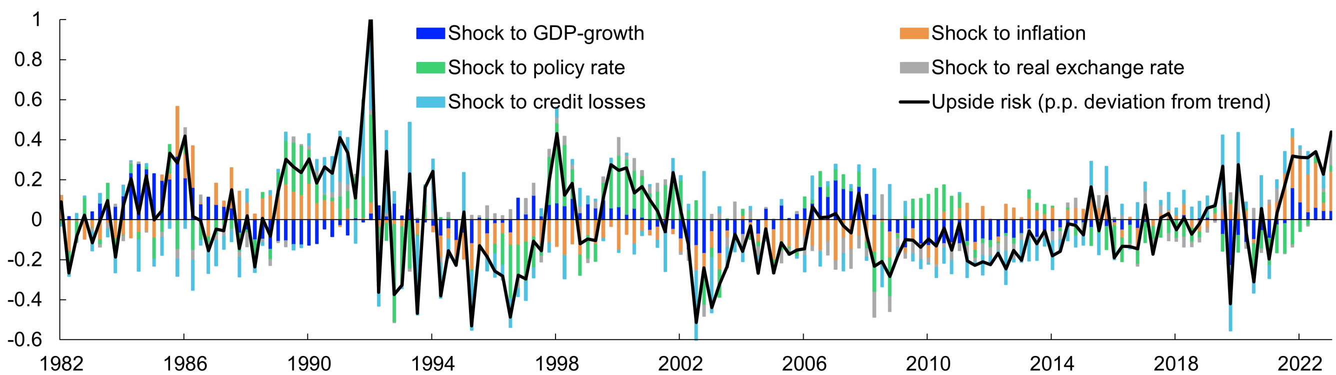
The lines show the predicted distribution based on data two quarters and one year earlier, respectively. Banks' credit losses are reported with a positive sign. The estimation period is 1981Q4-2023Q4.
Source: Norges Bank

[37] The reduced uncertainty in the two-quarters-ahead forecast is to be expected, given the shorter forecast horizon.

[38] Several other mitigating measures outside our framework contributed to the lower credit losses during the pandemic. Public measures helped many businesses to pay their bills and continue to operate. Payment deferrals offered by banks also helped businesses to survive liquidity shortfalls.

To better understand the underlying drivers of the upside risk in the one-year-ahead distribution, Chart 14 shows the historical shock decomposition of the upside risk one year ahead. Compared to the historical shock decomposition of the linear model, a larger share of the the upside risk variation is attributed to macroeconomic shocks (compare Chart F.1b and Chart 14). It is important to note that, unlike the linear VAR framework, macroeconomic shocks in the quantile regression do not directly drive credit losses. Instead, they give an indication whether credit loss spikes – when they occur – are likely to be more or less severe.

Chart 14: *Shock decomposition of the upside risk in credit losses/ATA. Percentage points*



One-year-ahead forecast at that point in time. The estimation period is 1981Q4-2023Q4.
Source: Norges Bank

The shock decomposition highlights key drivers behind several historical shifts in the upside risk:

1. In the period leading up to and during the Norwegian banking crisis (1984-1992), shocks to the policy rate and inflation contributed significantly to elevated upside risk.

2. After the Norwegian banking crisis (from 1993), reduced inflationary pressures helped reduce upside risk, while shocks to the policy rate increased upside risk between 1998 and the early 2000s (see green bars in Chart 14).

3. In the period leading up to and during the pandemic in 2020, low inflationary pressure combined with negative policy rate shocks reduced upside risk. However, in the aftermath, rising inflationary pressure pushed upside risk back to levels not seen before the 2000s.

7.2 Tail projections of credit losses as relevant benchmarks for stress testing

Quantile regressions are particularly well-suited to capture the behaviour of extreme outcomes, such as those observed during periods of financial stress. By modelling the upper quantiles of credit losses, quantile regressions enable the creation of realistic and data-driven benchmarks for adverse economic scenarios. These benchmarks can then serve as inputs for stress testing frameworks, improving the accuracy and credibility of risk assessments under severe yet plausible conditions.[39]

Based on the adverse scenario outlined in the Financial Stability Report 1/24 (FSR 1/24), we used our model results to project the 95th percentile of banks' credit losses in percent of ATA (Chart 15). The adverse scenario reflects a severe global supply shock, resulting in heightened inflationary pressures and elevated interest rates in Norway. In the report, the resulting credit losses are described as a 'tail-in-tail' event: First, the deep recession is a tail event, and given this, the outcome for credit losses is again a tail event (see dash-dotted black line in Chart 15a showing credit losses in the FSR 1/24 stress test).

Indeed, our quantile VAR-model indicates a significant increase in the 95th percentile of credit losses relative to ATA under this adverse scenario (see red solid line in Chart 15a). Notably, this increase builds upon an already elevated level in 2023, as shown in Chart 13b. Although both the linear and median projections remain relatively modest, the upside risk – measured as the gap between the 95th percentile and the median – shows a marked increase. Moreover, the 95th percentile indicates tail losses at a level comparable to those reported in FSR 1/24.

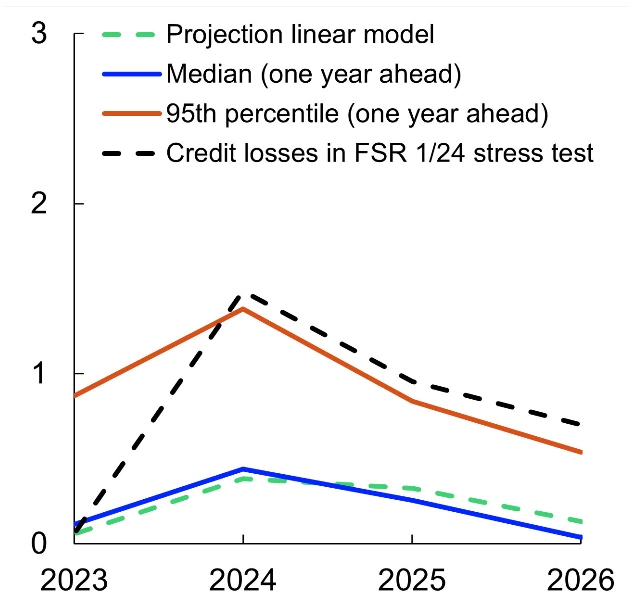
In Chart 15a, we assume that the realised recognised credit losses[40] align with the linear model projections. However, Chart 15b illustrates how realised tail credit losses may further amplify the 95th percentile. Specifically, in Chart 15b, we assume that the 95th percentile of credit losses fully materialises in the first year of the adverse scenario.[41] Furthermore, the exercise assumes that the one-year-ahead 95th percentile credit losses are realised immediately, triggered by a sudden increase in system-wide stress and banks' forward-looking behaviour under the current accounting regime. This assumption intensifies both the 95th percentile projection and the median (Chart 15b). This shift is consistent with the results shown in the fourth column of Chart 12, where an unexplained increase in credit losses drives an upward shift in the entire distribution of credit losses. (This pattern aligns with the illustrative example in Chart 9a.)

[39] As discussed in Sections 1 and 8 caution should still be exercised when relying on only one approach to determine credit losses. This analysis is for educational purposes and is not intended to provide an exhaustive model for credit losses in a stress test. Model uncertainty should still be taken into account, meaning that no single model is the only true model.

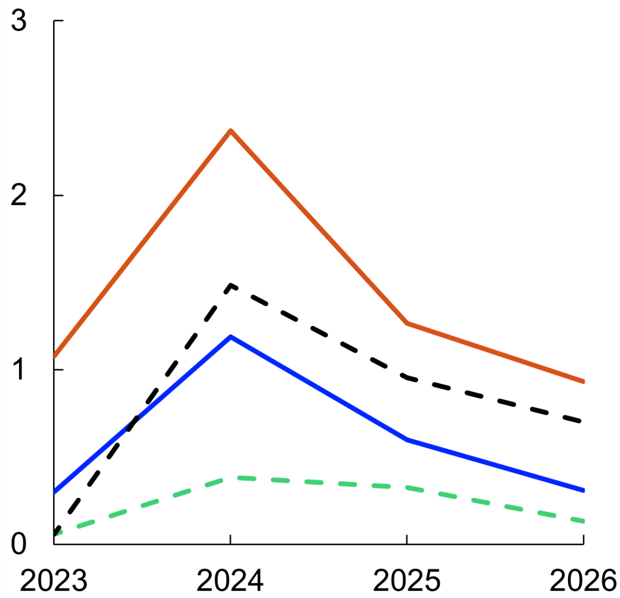
[40] Recognised credit losses refer to those reported in banks' income statements, as distinct from actual credit losses. See the discussion in Section 2.

[41] This assumption applies exclusively to the first year of the stress test exercise. For subsequent years, realised credit losses are assumed to follow the median projection.

Chart 15: *Example of how quantile regressions can be used as benchmarks for credit losses in the FSR 2024/1 stress test. Credit losses in percent of ATA.*



(a) *Realised losses based on linear approach*



(b) *Realised losses based on the 95th percentile*

Source: Norges Bank

8 Concluding remarks

Based on 40 years of data on banks' credit losses, we examine the factors that have historically affected developments in credit losses relative to ATA. By using a VAR model that includes the most relevant macro variables, we confirm that credit losses are negatively correlated with activity. We address model uncertainty by demonstrating that quantile regressions allow us to distinguish between responses at the centre of the distribution (median losses) and those in the tail (peak credit losses). Concentrating on tail-risk dynamics, we find that short-term upside risk in credit losses is predominantly driven by inflation and policy rate shocks.

One clear limitation of our analysis is the focus on aggregate bank credit losses across banks. By using panel data with individual banks or banking groups, we could uncover how different bank characteristics affect credit losses in the linear VAR framework. This could provide useful information on the bank-specific drivers of certain credit loss peaks and clarify whether they are related to specific banking groups. A panel study could also shed light on the importance of banks' risk management in determining the level and volatility of bank credit losses. By expanding the quantile regression to a panel of banks, we could also uncover any heterogeneity in the upside risk response.

Moreover, while our analysis covers the credit loss tail reaction (linearly) to macroeconomic shocks, it does not explicitly capture nonlinear dependencies between high credit losses and severe macroeconomic events. For example, households and firms may withstand minor or short-term shocks due to financial buffers, but a sharper or prolonged drop in activity, or a large increase in debt servicing costs, could trigger a "cliff effect", where tail credit losses rise disproportionately. This limitation may lead to underestimation or overestimation of credit losses during severe downturns. Expanding the model to better capture such nonlinear tail dependencies could enhance insights into adverse scenario dynamics.

In addition, our analysis fails to give reason for the exact timing of realised credit loss spikes. Our macro and financial variables provide some signals, but other higher-frequency data and/or more forward-looking indicators could potentially pick up these shifts in economy-wide risk more effectively.

Lastly, in this Memo, we focus on the effects of macroeconomic factors on credit losses, but our framework also allows for the study of feedback effects from credit losses back to the macroeconomy. Our model shows that increased losses have negative effects on GDP-MN growth (first row, fourth column in Chart 7). An in-depth analysis of this channel could provide valuable insights into how disruptions in the banking sector may affect the wider economy. Furthermore, our analysis reveals that credit losses exhibit non-linear dynamics. This suggests that a framework capable of capturing nonlinear effects is equally important for understanding the feedback mechanisms to the macroeconomy.

This analysis is intended to provide an educational overview by illustrating how the results are affected by different types of model extensions. The key takeaway is the critical importance of accounting for model uncertainty, particularly when addressing variables with nonlinear dynamics such as credit losses. In practice, the most effective approach may involve combining multiple extensions within a single model or leveraging a range of models, each offering unique insights, to better inform macroprudential policy. However, relying on a single model for credit loss predictions may provide a false sense of security. Therefor, any framework should be continuously updated and challenged based on new information and insights.

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Appendix

A Lenders' credit losses as nonlinear functions of borrowers' net value

A bank's return from lending to a project (interest rate earnings minus credit losses) is inherently nonlinear in the borrower's project returns (or collateral value): The lender must carry the downside risk by potentially being hit with credit losses, but has no stake in the upside risk of the individual project, because the typical loan contract does not link the interest payment to the project outcome or the collateral value (this is a defining property of a loan contract, in contrast to an equity stake). This nonlinearity is well known in the literature, see Chart A.1, inspired by a similar graph in the review by Chan-Lau (2011).

This nonlinearity of the return on a loan contract in project return (or collateral value) may be stated formally: assume that the realised value of the borrower's project (or the collateral value) is given by A, and the loan size is D. The net return of the bank if the project is successful (that is, if $A > (1+r)D$ and hence the loan with interest is repaid in full with interest), is given by rD. r is the net interest rate charged by the bank. If the project is less successful, the net return of the bank is less than rD, and given by $V = A - D$. Here, we assume that the lender recovers the full project value A in case the borrower defaults on the loan. This means that the lender's net return after any credit losses is given by a nonlinear function of the project return:

$$V = min[(A - D), rD]. \tag{A.1}$$

Now, assume that the value A of the project (or the collateral value) is stochastic and given by $A_i = A_* + \epsilon$, where ϵ has a standard normal distribution and A_* is the expected value of A_i.The net return of the bank (when the interest rate return is assumed to be zero for simplicity[42]) is given by $V = A_i - D$ if $A_i < D$ and zero otherwise. If we now reverse the sign, so that credit losses are positive numbers, the bank's credit losses (negative return) is given by

$$L_i = -V_i = -(min[(A_i - D), 0]). \tag{A.2}$$

If we sum over a set of loans of equal size to different firms (10 000 loans), and simulate a certain distribution for ϵ, and also report loan losses as a percent of loans (L_i/D) for a whole *range* of expected project returns A_*, we get a smoother graph as shown by the blue curve in A.2. In the example illustrated in the chart, $D = 100$ for all loans, expected returns A_* are in the range from 100 to 400, the distribution of ϵ is normal with a standard deviation of 20, and the lender recovers 80 percent of the project value (or collateral value) in case of bankruptcy ($L_i = -V_i = -(min[(0.8 * A_i - D, 0]))$.

[42] The optimal loan contract would usually include a higher r when risk is higher.

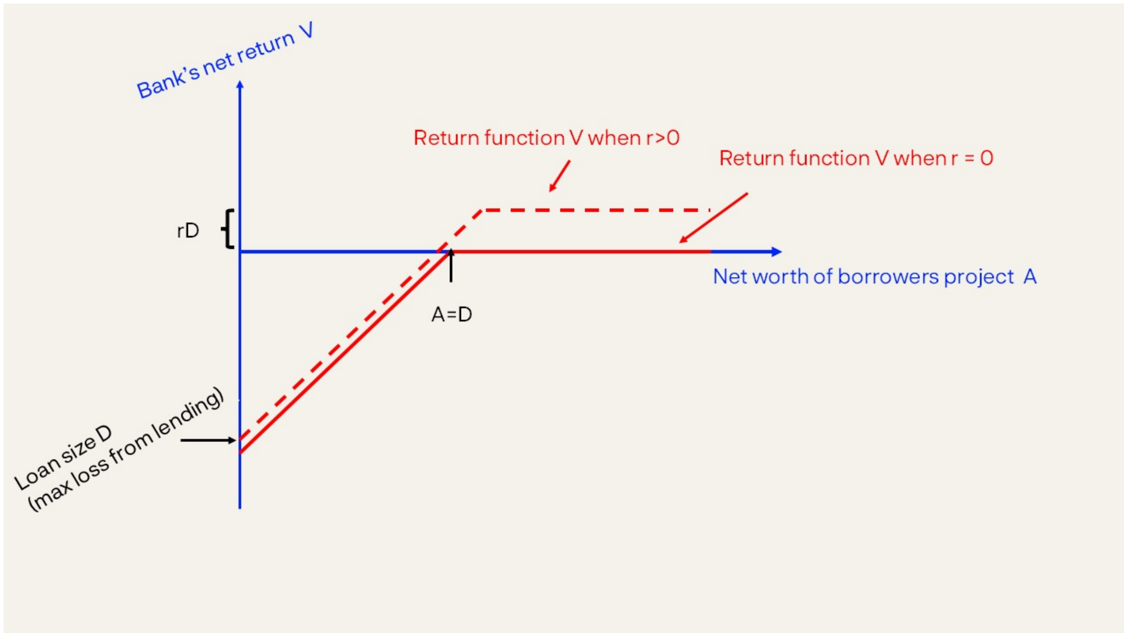
A simple nonlinear but differentiable function can be used to represent an approximation to this type of expected loan losses on a portfolio of loans, as a function of a common factor like expected project returns or collateral values A, see e.g. page 23 in Buncic et al. (2019). Collateral values or project incomes are often correlated with aggregate indicators for property prices or GDP growth rates, suggesting a similar nonlinear relationship between credit losses and macroeconomic variables at an aggregate level, where for example, GDP growth is on the x-axis and the banking sector wide credit loss ratio is on the y-axis.

Could loss reversals change this picture? Accounting standards determine the timing of credit losses, for example the degree of front-loading of expected losses and later corresponding reversals should not all expected losses be realised. Thus, in individual periods, banks' credit losses may be negative. But accumulated losses over the lifetime of each loan will typically be a positive nonlinear function of the project return (or collateral value). Using the previous example, assuming that the initial estimate of A is too low and that the initially recorded credit loss is too large(see the blue curve). If so, a correction needs to be made in the subsequent period when the loan is repaid. This will reduce total losses. However, the final assessment of L, after corrections, is also given by the expression A.1 above, where we now interpret the A's as being the final values and not the preliminary values. After corrections, the distribution of *accumulated* losses over loans' lifetimes is still nonlinear in the (true) project outcomes, shown by the red dashed line in Chart A.2.

In order to further study the aggregate performance of loan portfolios, a copula model is often used. Copula models capture the influence of the joint distribution of shocks to project performance on the tail risk, see for example ECB (2019). When project performance across a portfolio of loans is correlated, tail risk may be much higher than in the case of independent distributions assumed in this simple example. Systemic risk is typically analysed in a setting where bad outcomes across projects – or across sectors or institutions – are correlated.

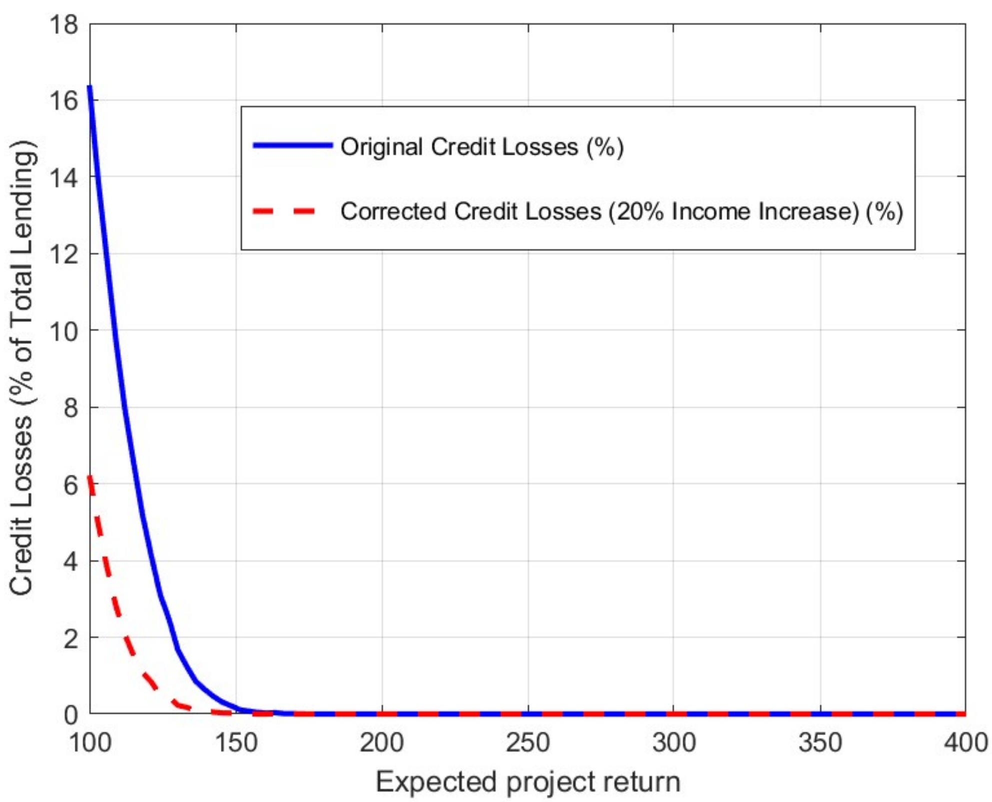
The graph in Chart A.2 shows that the unconditional expectation of losses (across different expected project returns A_*) is higher than the loss given a certain expected project return A_*, due to the nonlinearity of losses as a function of project returns (and Jensen's inequality). This suggests that the unconditional expectation of credit losses will increase with the volatility of project returns (or asset values). Just as equity owners in a project with some leverage benefit from higher project return volatility given limited liability, lenders benefit from lower volatility.

Chart A.1: *The return from a loan contract is inherently nonlinear in the value of the project*



Source: Norges Bank

Chart A.2: *Simulation of credit loss ratio of a portfolio of loans of size 100, as a function of increasing mean project returns.*



Source: Norges Bank

B Properties of the data

Table B.1: *Summary statistics of main time series*

Variable:	Credit loss/ATA (%)	GDP-MN growth (%)	Inflation (%)	Policy rate (%)	Real exch. rate
Period[1]:	1992Q4-2023Q4 (1981Q4-2023Q4)	1992Q4-2023Q4 (1981Q4-2023Q4)	1992Q4-2023Q4 (1981Q4-2023Q4)	1992Q4-2023Q4 (1981Q4-2023Q4)	1992Q4-2023Q4 (1981Q4-2023Q4)
Mean	0.16 (0.37)	2.55 (2.32)	2.00 (3.11)	3.17 (5.49)	94.20 (93.15)
Median	0.09 (0.15)	2.40 (2.29)	1.90 (2.37)	2.29 (4.50)	95.22 (92.53)
St.dev.	0.31 (0.56)	2.18 (2.25)	1.12 (2.50)	2.42 (4.50)	6.09 (5.67)
Max	1.94 (2.63)	7.67 (7.67)	6.48 (11.41)	12.74 (15.49)	110.75 (110.75)
Min	-0.27 (-0.27)	-7.72 (-7.72)	0.16 (0.16)	0.00 (0.00)	82.95 (82.95)

1 Numbers in parentheses apply to the period 1981Q1-2023Q4. We cross check empirical results for this time period.

Sources: Statistics Norway, S&P Capital IQ, OECD and Norges Bank

The properties of the data may also be described in terms of Granger causality between variables. The right column indicates the probability of the null hypothesis, based on five lags. The table suggests that the policy rate is useful for predicting credit losses, and credit losses are useful for predicting GDP growth.

Table B.2: *Granger causality between main variables. Five lags. Same time periods as in previous tables.*

Null hypothesis	Probability
GDP-MN growth does not Granger cause credit losses/ATA	0.93 (0.82)
Credit losses/ATA does not Granger cause GDP-MN growth	0.00 (0.00)
Policy rate does not Granger cause credit losses/ATA	0.00 (0.03)
Credit losses/ATA does not Granger cause policy rate	0.00 (0.02)
Real exchange rate does not Granger cause credit losses/ATA	0.94 (0.73)
Credit losses/ATA does not Granger cause real exchange rate	0.49 (0.46)
Inflation does not Granger cause credit losses/ATA	0.68 (0.39)
Credit losses/ATA does not Granger cause inflation	0.19 (0.59)

C Model specification

Our core model is a VAR-model estimated with GDP-MN growth, CPI-ATE inflation, the policy rate, the real exchange rate and credit losses in percent of ATA. The specification is with four lags, quarterly data from 1992Q4 to 2023Q4. Tests for lag specification are documented in Table C.1.

Table C.1: *Lag selection criteria*

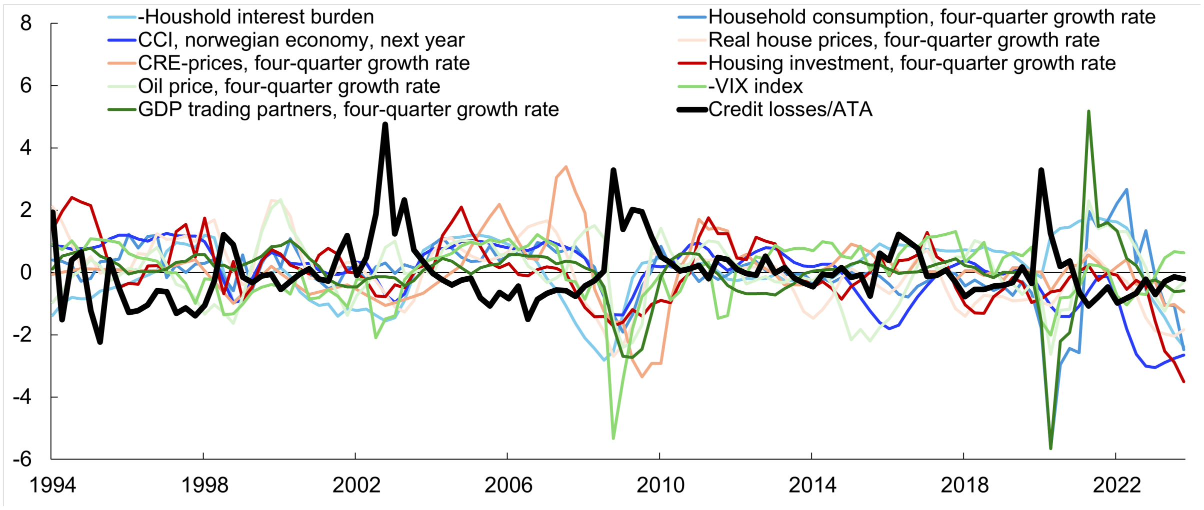
Lag	LR	AIC	SC	HQ
0	NA	17.655	17.769	17.702
1	1058.831	9.086	9.768*	9.363
2	108.853	8.525	9.776	9.034*
3	39.93	8.559	10.379	9.298
4	43.744	8.538	10.926	9.508
5	65.758*	8.270*	11.227	9.471
6	30.961	8.34	11.865	9.772
7	21.727	8.496	12.59	10.159
8	29.849	8.54	13.203	10.434

The (*) indicates lag order selected by criterion. LR: Sequential modified LR test statistic (each test at 5 percent level). AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion.

D Model robustness - Alternative specifications

There is significant uncertainty regarding which variables and transformations should be included to best capture historical relationships. This uncertainty highlights the importance of exploring alternative model specifications. We select indicators that are motivated both theoretically and empirically (see Section 3 for a detailed discussion). Most of these indicators tend to increase or decrease during periods of heightened credit losses (Chart D.1).To address model uncertainty, we estimate multiple models with different indicators, time frames, and lag structures.

Chart D.1: *Alternative financial and economic variables*



Variables are standardised by subtracting the average and dividing by the standard deviation. Average and standard deviation are calculated for the period from 1994Q1 to 2023Q4.
Sources: Bloomberg, CBRE, DN, Eiendom Norge, Finn.no, FRED, JLL, Kantar TNS, OPAK, Real estate Norway, Statistics Norway S&P Capital IQ, Thomson Reuters, OECD and Norges Bank

Table D.1 reports the peak response of credit losses, expressed as a percentage of ATA, to key macroeconomic shocks across the models. To examine the persistence of the credit loss response, the table also includes the average level over the two subsequent years. The results remain robust across a wide range of model specifications. An exception is observed in the response to a policy rate shock when the sample is extended to include the Norwegian banking crisis period (see second row in Table D.1), which is discussed further in Section 6.1.1.

Below the second line in Table D.1, we present results from three model extensions that include time series data for key bank-specific variables. These variables are intended to reflect improvements in bank risk management, which likely reduced credit losses. Although difficult to quantify, a comprehensive analysis would ideally account for differences at the bank level and additional indicators, see discussion in Section 8. Nonetheless, Table D.1 illustrates that the responses of key macroeconomic shocks remain robust, even when incorporating simple measures of risk on banks' balance sheets.

Below the third line in Table D.1, we demonstrate that our results are robust against alternative measures of credit losses as a percentage of ATA. Neither measuring credit losses as a percentage of gross lending nor expanding the analysis to include all banks and mortgage companies materially alters the sign or magnitude of the responses.

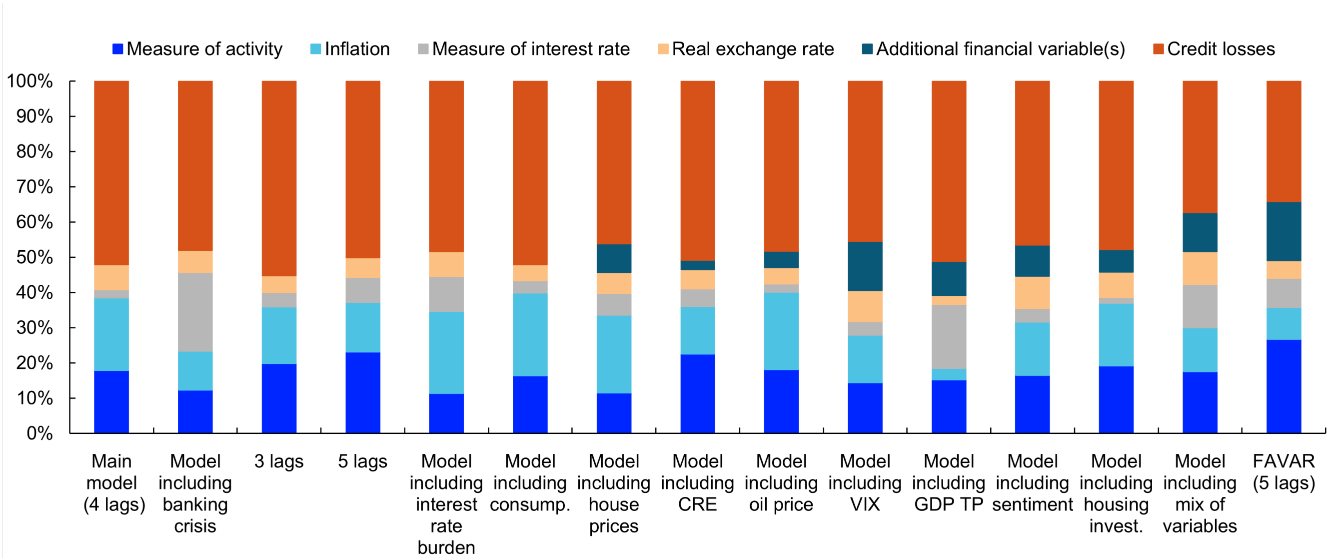
Table D.1: *Response in credit losses/ATA to key macroeconomic shocks. Measured as annualised percentage point deviation from long-term equilibrium*

Model version	GDP-MN shock[1] Max[4]	GDP-MN shock[1] Mean[5]	Inflation shock[2] Max[4]	Inflation shock[2] Mean[5]	Policy rate shock[3] Max[4]	Policy rate shock[3] Mean[5]
Baseline model	0.05	0.01	0.08	0.03	0.02	0.01
Model including banking crisis	0.03	0.01	0.06	0.06	**0.10**	**0.09**
Model with 3 lags	0.04	0.01	0.08	0.05	0.03	0.02
Model with 5 lags	0.05	0.01	0.07	0.05	0.05	0.01
Model including interest rate burden	0.04	0.01	0.09	0.04	0.06	0.03
Model including consumption	0.02	0.01	0.11	0.07	0.02	0.00
Model including house prices	0.04	0.01	0.10	0.03	0.05	0.02
Model including CRE prices	0.05	0.02	0.08	0.05	0.05	0.02
Model including oil price	0.05	0.01	0.09	0.07	0.02	0.01
Model including VIX index	0.04	0.01	0.08	0.02	0.03	0.01
Model including GDP TP	0.03	0.01	0.09	0.04	0.03	0.02
Model including sentiment	0.05	0.01	0.10	0.04	0.03	0.01
Model including housing investment	0.05	0.01	0.09	0.04	0.02	0.01
Model including mix of variables	0.05	0.01	0.06	0.03	0.06	0.02
FAVAR model	0.05	0.01	0.09	0.04	0.06	0.01
Model including equity ratio	0.05	0.01	0.08	0.03	0.02	0.01
Model including lending mix	0.05	0.01	0.08	0.04	0.05	0.02
Model including lending rate	0.04	0.01	0.09	0.03	0.04	0.02
Model including credit losses/lending	0.06	0.02	0.10	0.04	0.02	0.01
Model - all banks and mortage companies	0.04	0.01	0.07	0.06	0.04	0.01

1 GDP-MN growth shock normalised to a one percentage point ***decrease*** *in the growth rate.*
2 CPI-ATE inflation shock normalised to a one percentage point increase in inflation.
3 Policy rate shock normalized to a one percentage point increase in the policy rate.
4 Peak response of credit losses relative to ATA.
5 Average credit losses relative to ATA over the two years following and including the peak.
Baseline model: *The model includes GDP-MN growth, inflation, policy rate, real exchange rate, and credit losses/ATA. The estimation period spans from 1992 Q4 to 2023 Q4. The linear model is described in detail in Section 4.*
Model including banking crisis: *An extension of the baseline model with an expanded estimation period from 1981 Q4 to 2023 Q4.*
Model with 3 lags: *The baseline model modified to include three lags.*
Model with 5 lags: *The baseline model modified to include five lags.*
Model including interest rate burden: *An adjustment to the baseline model where the interest rate burden replaces the policy rate.*
Model including consumption: *An adjustment to the baseline model where four-quarter consumption growth replaces four-quarter GDP-MN growth.*
Model including house prices: *The baseline model extended to include four-quarter growth in real house prices as an additional endogenous variable.*
Model including CRE: *The baseline model extended with four-quarter growth in real commercial real estate (CRE) prices as an additional endogenous variable. Additionally, the five-year risk-free rate replaces the policy rate.*
Model including oil price: *The baseline model extended to include four-quarter growth in real oil prices as an additional endogenous variable.*
Model including VIX index: *The baseline model extended to include the log of the VIX index as an additional endogenous variable.*
Model including GDP TP: *The baseline model extended to include GDP for Trading Partners (TP) as an additional endogenous variable.*
Model including sentiment: *The baseline model extended to include the Consumer Confidence Index (CCI) reflecting expectations of the Norwegian economy one-year ahead as an additional endogenous variable.*
Model including housing investment: *The baseline model extended to include four-quarter housing investment growth as an additional endogenous variable.*
Model including mix of variables: *A variation of the baseline model with CCI and real CRE prices added as endogenous variables. Real oil prices and the VIX index are included as exogenous variables.*
FAVAR: *A Factor-Augmented Vector Autoregression model based on the baseline model, extended with the first two common components of all financial variables as additional endogenous variables. Model modified to include five lags.*
Model including equity ratio: *The baseline model extended to include the break-adjusted time series for the seven large banks' equity ratio as an additional endogenous variable.*
Model including lending mix: *The baseline model extended to include banks' and mortgage companies' corporate lending as a share of total retail and corporate lending as an additional endogenous variable.*
Model including lending rate: *An adjustment to the baseline model where banks' and mortgage companies total lending rate replaces the policy rate.*
Model including credit losses/lending: *An adjustment to the baseline model where banks' credit losses as a share of gross lending to customers replace credit losses as a share of ATA. To ensure comparability, the time series is standardised to match the mean and standard deviation of credit losses in percent of ATA.*
Model including all banks and mortgage companies: *An adjustment to the baseline model where banks' credit losses as a share of ATA are based on all banks and mortgage companies. To ensure comparability, the time series is standardised to match the mean and standard deviation of credit losses in percent of ATA.*

E Variance decomposition of alternative models

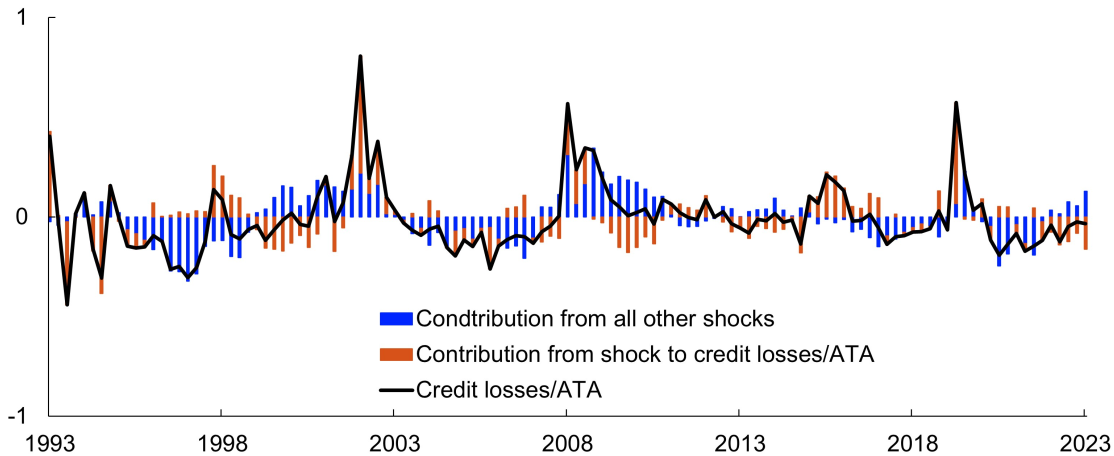
Chart E.1: *Share of variation in credit losses explained by shocks to each variable. 40 quarters ahead. Percent.*



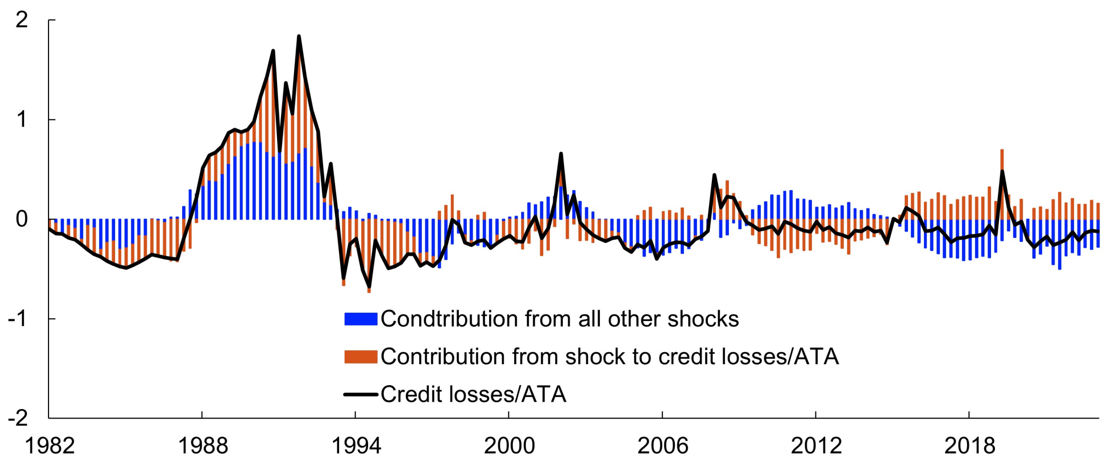
Baseline model: *The model includes GDP-MN growth, inflation, policy rate, real exchange rate, and credit losses/ATA. The estimation period spans from 1992 Q4 to 2023 Q4. The linear model is described in detail in Section 4.*
Model including banking crisis: *An extension of the baseline model with an expanded estimation period from 1981 Q4 to 2023 Q4.*
Model with 3 lags: *The baseline model modified to include three lags.*
Model with 5 lags: *The baseline model modified to include five lags.*
Model including interest rate burden: *An adjustment to the baseline model where the interest rate burden replaces the policy rate.*
Model including consumption: *An adjustment to the baseline model where four-quarter consumption growth replaces four-quarter GDP-MN growth.*
Model including house prices: *The baseline model extended to include four-quarter growth in real house prices as an additional endogenous variable.*
Model including CRE: *The baseline model extended with four-quarter growth in real commercial real estate (CRE) prices as an additional endogenous variable. Additionally, the five-year risk-free rate replaces the policy rate.*
Model including oil price: *The baseline model extended to include four-quarter growth in real oil prices as an additional endogenous variable.*
Model including VIX index: *The baseline model extended to include the log of the VIX index as an additional endogenous variable.*
Model including GDP TP: *The baseline model extended to include GDP for Trading Partners (TP) as an additional endogenous variable.*
Model including sentiment: *The baseline model extended to include the Consumer Confidence Index (CCI) reflecting expectations of the Norwegian economy one-year ahead as an additional endogenous variable.*
Model including housing investment: *The baseline model extended to include four-quarter housing investment growth as an additional endogenous variable.*
Model including mix of variables: *A variation of the baseline model with CCI and real CRE prices added as endogenous variables. Real oil prices and the VIX index are included as exogenous variables.*
FAVAR: *A Factor-Augmented Vector Autoregression model based on the baseline model, extended with the first two common components of all financial variables as additional endogenous variables. Model modified to include five lags.*
Source: Norges Bank

F Shock decomposition of the linear VAR model

Chart F.1: *Historical decomposition of developments in credit losses/ATA as a percentage point deviation from a trend* [1]*. The bars show contributions from the shocks (innovations) in the VAR model. Annualised percentage points deviation*



(a) *Excluding the Norwegian banking crisis*

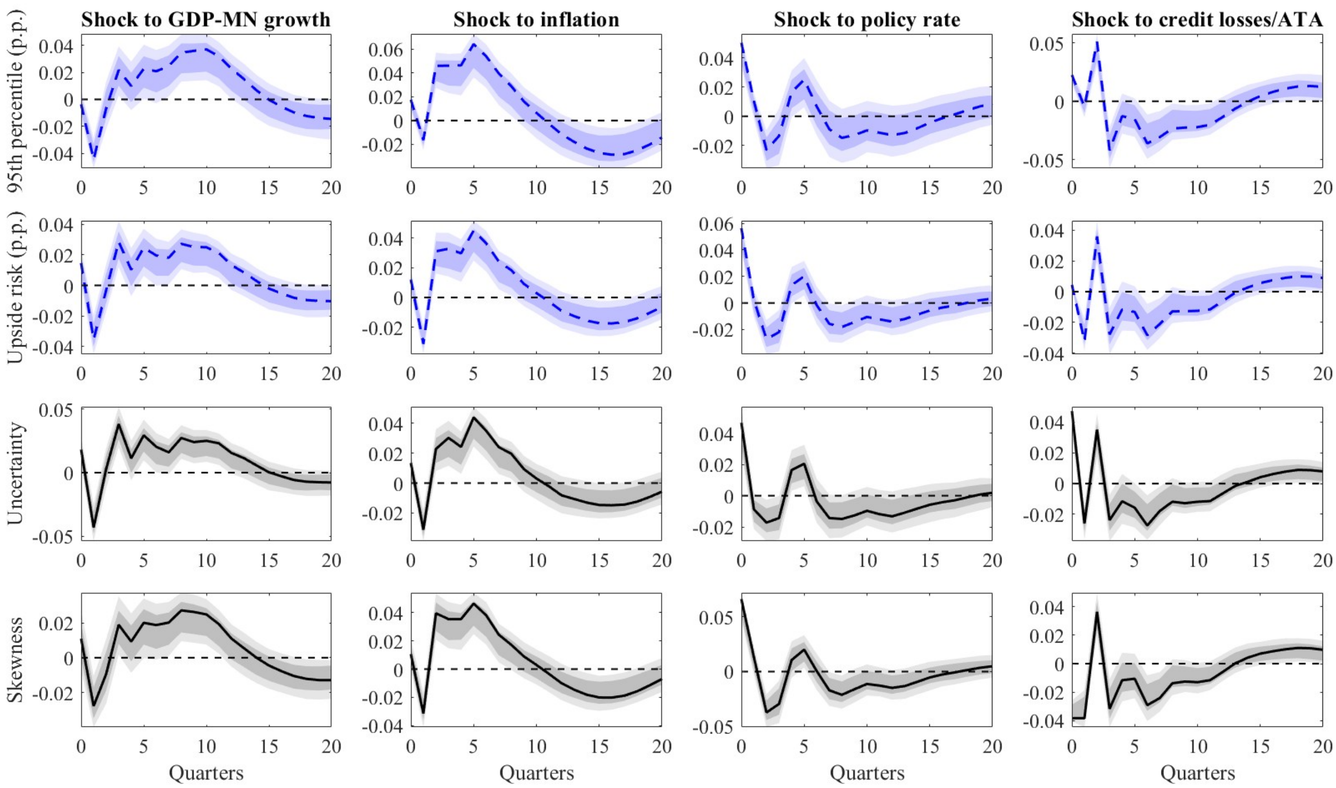


(b) *Including the Norwegian banking crisis*

1 The trend is the estimate from the VAR model, conditioned on information available in 1992 Q4 (for the first chart) and 1981 Q4 (for the second chart). That is, these trends are the non-stochastic contributions, starting from these initial conditions.
"Contribution from all other shocks" are the sum of the contribution from shocks to GDP-MN growth, inflation, the policy rate and the real exchange rate.
Source: Norges Bank

G Two-quarters-ahead responses of the distribution of credit losses

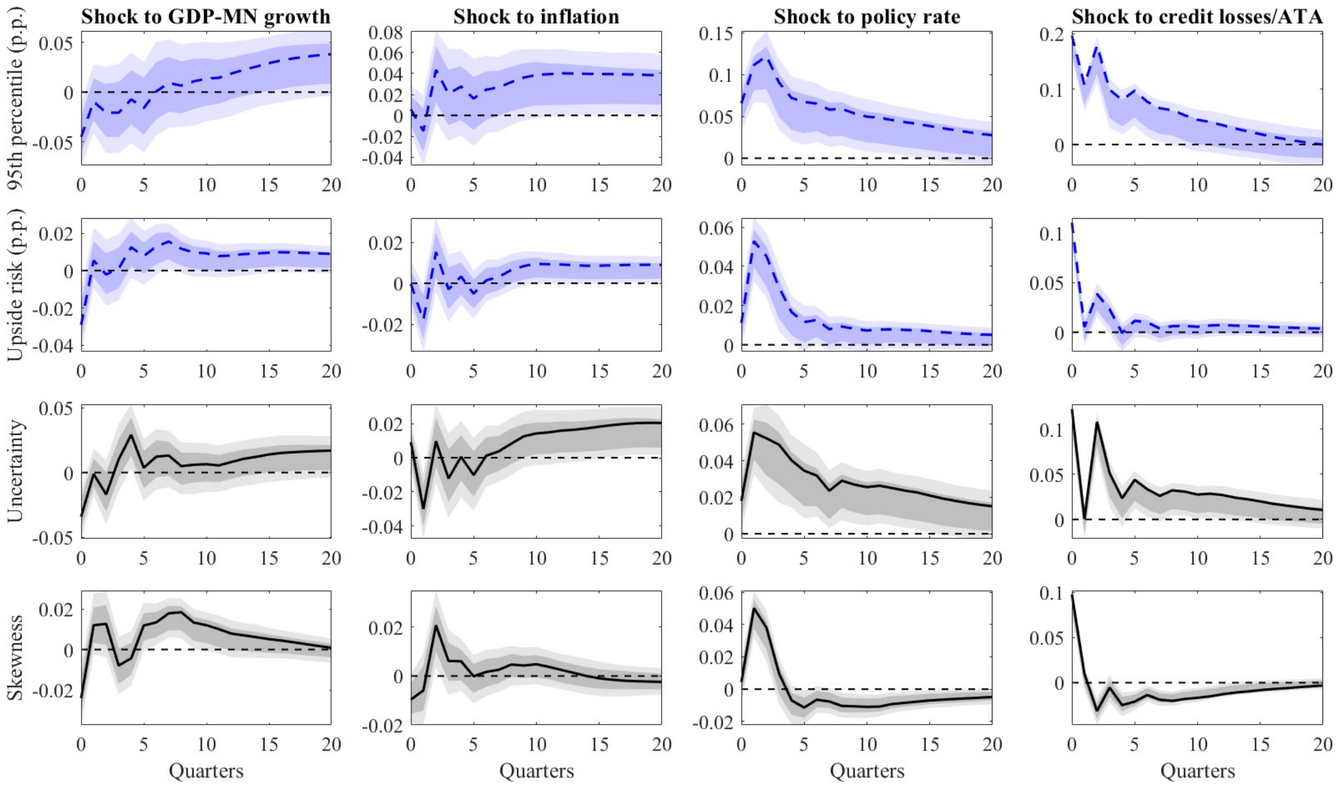
Chart G.1: *Two-quarter-ahead responses of the 95th percentile, upside risk, uncertainty and skewness - Norwegian banking crisis excluded*



The impulse responses of the 95th percentile, the upside risk, the uncertainty, and skewness of credit losses as a percentage of ATA, following a one-standard-deviation shock to the respective variables. Upside risk is defined as the difference between the 95th percentile and the median. The shaded regions represent the 90% and 68% confidence intervals, indicating the uncertainty around the estimated responses. The estimation period is 1992Q4-2023Q4.

Source: Norges Bank

Chart G.2: *Two-quarter-ahead responses of the 95th percentile, upside risk, uncertainty and skewness - Norwegian banking crisis included*



The impulse responses of the 95th percentile, the upside risk, the uncertainty, and skewness of credit losses as a percentage of ATA, following a one-standard-deviation shock to the respective variables. Upside risk is defined as the difference between the 95th percentile and the median. The shaded regions represent the 90% and 68% confidence intervals, indicating the uncertainty around the estimated responses. The estimation period is 1981Q4-2023Q4.

Source: Norges Bank