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Beyond the crystal ball: forecasting non-performing loans.

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Key findings[1]

- Non-performing loans (NPLs) are where the borrower has defaulted on a loan and the lender is likely to incur some losses. The proportion of total loans that are non-performing is a key indicator of the quality of a lender's assets and the overall health of the financial system.
- NPLs are affected by the general state of the economy. For instance, an economic recession and rising unemployment would likely lead to financial strain for indebted households and businesses, which could cause them to default on their debt. This paper examines this relationship to assess whether macro-economic conditions can be a useful predictor of future changes in NPLs.
- To conduct this analysis a range of linear time-series models are used to project the share of non-performing loans across bank lending. These models incorporate many of the macro-economic variables commonly used in the literature such as unemployment, house price inflation and the average debt servicing to income ratio.
- The results suggest that the models are reasonably good at explaining movements in NPLs in sample, with the Bayesian VAR model providing the best out-of-sample forecast performance. This is notable because of the lack of volatility and high level of persistence in NPLs which often means out-performing simple forecasting models can be difficult.
- We can leverage additional approaches to explain future movements in NPLs using earlier stage financial distress data. Housing lending arrears appear to be a good near-term predictor of housing NPLs.
- Interest rates and debt servicing to income ratios are included in the models, however, it may be hard for them to accurately predict the impact of high interest rates on NPLs because high interest rates have tended to happen when the economy has been strong. As such, a different approach is needed for this. This note provides some results from a sensitivity included in the Reserve Bank's 2022 Bank Solvency Stress test that showed banks' estimates of mortgage defaults at differing levels of interest rates. The key finding from this was that defaults are likely to become more acute as interest rates move above the original affordability test rates.

[1] The author would like to thank colleagues across the RBNZ for their insights, discussion and feedback.

1. Introduction

This paper examines the relationship between non-performing loans and economic conditions. This relationship is used to forecast the possible path of non-performing loans (NPLs) and provide a useful input into the Reserve Bank of New Zealand's (RBNZ's) assessment of financial stability risks.

Non-performing lending is a key indicator of the quality of lending institutions' (i.e. banks and/or non-bank lenders) assets and the health of the financial system. Currently, high interest rates and the resulting debt servicing stress for borrowers means that projecting this lending is important for understanding the potential impacts on the financial system. While there have been numerous studies in other countries and by trading banks analysing the drivers of NPLs and using models to forecast them, this appears to be the first published study on New Zealand data.

The rest of the *Note* is organised as follows. Section 2 describes what NPLs are and their recent history in New Zealand. Section 3 outlines the relevant literature which has already explored this topic. Section 4 explores the data used in the analysis whilst section 5 outlines the methodological approach. Section 6 illustrates the empirical results alongside two short extensions to this analysis. Finally, section 7 provides a conclusion.

2. Background

Non-performing loans are lending where a financial institution is likely to incur some losses, i.e. the borrower is likely to default on the loan. The NPL ratio measures the value of NPLs compared to the value of total loans. The RBNZ pays particularly close attention to this metric in its regular *Financial Stability Report*. Whilst this metric is quite a lagged indicator of stress, it is important because lending that becomes non-performing and eventually defaults can result in a loss for the financial institution if the value of the seized collateral is insufficient to cover the value of the loan. An increasing or high NPL ratio illustrates that lenders are facing more defaults, which could reduce their profitability, their solvency and their ability to obtain funding. As a result, a large increase in NPLs could reduce lender's willingness and ability to continue supplying credit to households and businesses, which would have negative impacts on the real economy.

NPL ratios are impacted by the general state of the economy. Higher interest rates could result in borrowers facing budgetary constraints, forcing them to cut back upon discretionary expenditures or looking to increase their number of hours worked. Similarly, a deterioration in economic activity resulting in less revenue for businesses could also constrain business profit margins and erode cash reserves. If these deteriorations persisted, then temporary support measures provided by their lending institutions such as extending the term of the loan or switching to only making interest payments (instead of principal and interest) may be insufficient to prevent the borrower missing obligated repayments, eventually resulting in the lending becoming non-performing. Given this, we might expect a relationship between the current economic indicators and the outlook for NPLs.

Figure 1 shows the NPL ratio for total bank lending. It is notable how stable this series has been with the only large fluctuation in the aftermath of the Global Financial Crisis (GFC). Data limitations mean this only goes back to the mid-1990s; however, it is possible to obtain impaired lending (which excludes loans 90 or more days overdue) back to Q1 1990 from published bank disclosure statements (figure 2). This data was significantly higher in 1989-1990 when New Zealand experienced a banking crisis in the aftermath of the global stock market crash in 1987. During this period, New Zealand's largest trading bank required two recapitalisations by the Government in order to continue operating as an economic downturn, poor lending standards and minimal risk management practices resulted in substantial loan defaults (Hunt 2009). This period highlighted the significant impacts a rise in non-performing loans can have on lenders.

Figure 1: Non-performing lending as a share of total lending[2]

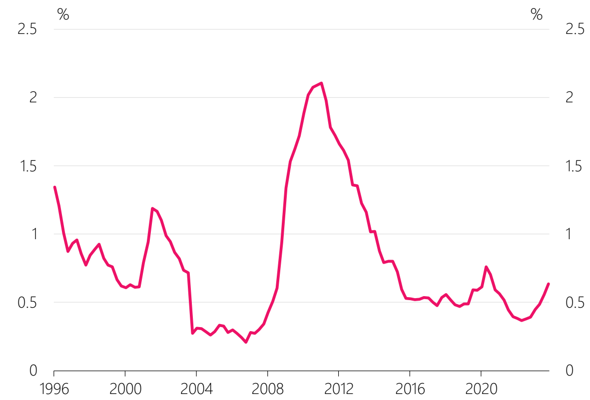
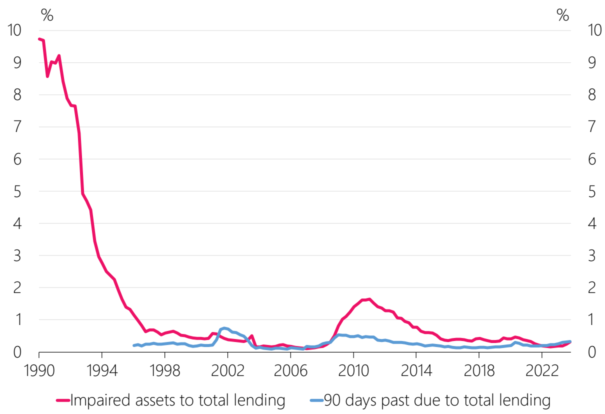


Figure 2: Impaired and 90 days past due lending as a share of total lending



3. Forecasting NPLs in the literature and in practice

There is limited published research that has modelled and forecasted NPLs in New Zealand. However, there are several published studies in international academic journals that forecast NPL ratios for a number of other countries using macro-economic variables with a range of methodologies and findings. A strand of the research uses time-series techniques to identify indicators – based on the state of the economy – that can help forecast a deterioration in bank asset quality. In some studies, macroeconomic variables are supplemented with bank-specific financial variables in a panel data approach (see Erdas and Ezanoglu (2022) and Louzis, Vouldis and Metaxas (2012)). These studies included corporate leverage, rates of return on assets (a proxy for bank management quality), cost efficiency (where higher cost efficiency could mean inadequate spending on borrower screening, which could subject banks to higher credit risk exposures in the future) and equity to asset ratios (a proxy for moral hazard). This study, however, focuses on only the significance of macroeconomic factors in explaining NPLs, and the impact of bank-specific indicators is left for future extensions to this work.

Several studies approach this topic using a country-specific Vector Auto-Regression (VAR) modelling approach. Babouček and Jančar (2005) use data from the Czech Republic to detail the interactions between loan loss and lending, unemployment rate, money supply, exchange rate, inflation, short-term interest rates and foreign trade flows. They find that an increase in unemployment and inflationary pressures leads to a deterioration in loan quality. Dinh, Mullineux and Muriu (2012) investigate the impacts of macroeconomic factors on secured and unsecured lending in the United Kingdom and find that changes in house prices, interest rates and unemployment rates have a significant impact on NPLs for secured lending. Only unemployment has a discernible impact on unsecured lending. Mascu and Pescu (2016) show that macroeconomic

[2] The Reserve Bank of New Zealand also collects data on NPLs of non-bank deposit takers (NBDTs) however this data series is not long enough to be included in the modelling. Furthermore, given the size of the NBDTs sector is very small relative to the banking sector, NBDTs account for just under 3% of intermediated credit, they are unlikely to significantly influence the results of this analysis.

variables have a significant effect on NPLs in Romania, with the lagged real interest rate having a significantly positive impact on NPLs. Finally, Gambera (2000) models loan quality as a function of unemployment rates, bankruptcy proceedings, business cycle indicators and borrower incomes. Similar to the studies above, it finds that unemployment alongside bankruptcy, income and housing permits can be good predictors of non-performing loans.

In addition to academic studies of the drivers of NPLs, banks model the impact of economic conditions on their asset quality for capital requirements and loan loss provisioning. However, this analysis is not usually published. Banks evaluate expected loan losses (defined as the average level of losses on lending that they expect to experience over time) and provision for these losses ahead of time as per IFRS9 standards. Provisioning is funding set aside by the bank to absorb the impact of future expected losses from defaulted loans (see ECB (2020) for more details). Loss provisioning models use a range of macroeconomic variables including unemployment rates, GDP growth, house prices, commercial property prices and inflation to determine the expected credit losses. These losses are also based on the bank's estimated losses over a range of economic scenarios (including a baseline, upside and downside scenarios), and the probabilities of each scenario occurring. In a specific year, however, losses may be higher or lower than the average level. In some cases, such as during an economic downturn, the number of borrowers unable to repay their loans may be significantly higher than average. The difference between the actual loss and the expected loss is called the unexpected loss. Banks manage their exposure to unexpected losses by holding capital, capital allocation and stress testing.

Banks will often conduct financial resilience modelling in addition to their 'top-down' loan provisioning modelling. This modelling utilises granular 'loan level' data to allow the lender to assess the likelihood of a borrower facing stress servicing their debt. This is done by determining the likelihood of an individual loan moving from stage 1 (performing) to stage 2 (underperforming) or stage 3 (non-performing). This dataset is extremely rich and would normally include variables about the debt and characteristics of the borrower. Currently, the RBNZ is working to collect loan level data from regulated entities such as banks to enable similar analysis, but this has not yet been finished.[3]

4. Data

This section describes the data used in the analysis. The variable being modelled is the quarter-on-quarter percentage change of the seasonally-adjusted NPL ratio. This series is formed from splicing together two datasets. Data from Q1 1996 to Q4 2017 is collected from General Disclosure Statements. This dataset complies data from all New Zealand's registered banks during this period, accounting for any mergers or new entrants to the industry to avoid any double counting. From Q1 2018 onwards data from the *Bank Balance Sheet survey* is used.[4] The differences between the series from the two sources over the overlapping period are very small. Having a longer dataset that spans multiple business cycles would be useful. Unfortunately, the RBNZ only started collecting NPL data in the mid-1990's, limiting the horizon for analysis.

NPL ratios are calculated using the following formula:

[3] For more information regarding the RBNZ's loan level data collection programme please refer to Loan-level data collection - Reserve Bank of New Zealand - Te Pūtea Matua (rbnz.govt.nz).
[4] For more information regarding the 'Bank Balance Sheet survey' please refer to Bank balance sheet survey - Reserve Bank of New Zealand - Te Pūtea Matua (rbnz.govt.nz).

$$NPL_t = \frac{Impaired\ loans_t\ +\ loans\ 90\ days\ or\ more\ overdue\ (but\ not\ impaired)_t}{Total\ lending_t}$$

Impaired loans are those loans when one or more events have occurred that cause the lender to believe that they will not receive all of the future principal or interest repayments that have been contractually agreed with the borrower. These events could include: the borrower entering significant financial difficulty or bankruptcy; the borrower failing to make repayments as required and the loan becoming past due; and/or the contractual agreement between the lender and borrower being restructured or amended. Impaired loans are reported separately from loans that are 90 days or more overdue to avoid double counting.

The analysis to forecast NPLs covers the period from Q2 1996 to Q4 2023. This is done using variables commonly used in the overseas literature to model non-performing loans. These are the unemployment rate, CPI inflation, house prices, the floating mortgage rate, OCR, household credit growth, output gap, trade-weighted-index (TWI) and the average mortgaged household's debt servicing ratio (see Appendix Table 1 for further information). These variables are sourced from Statistics New Zealand, CoreLogic New Zealand and the RBNZ. The floating mortgage rate is used because it can be backdated to 1996. Most borrowers would fix their lending for a period of 1-2 years, but fixed rate data can not be backdated as far.

All variables are tested for stationarity using Augmented Dickey-Fuller (ADF) unit root tests. The results of these tests suggest the variables are non-stationary in levels and so are differenced to make the data stationary.

5. Methodology

This section explains the modelling approach and forecasting procedures used. First, it describes the model structures used. Second, it describes the forecasting and forecast comparison process and presents the results. Forecasting methods include a Bayesian VAR, a time-varying-parameter Bayesian VAR, and a Bayesian VAR with conditional forecasts. A recursive pseudo out-of-sample forecasting experiment is carried out in this study to decide on whether economic data has some predictive power.

1. Modelling structures

a. Baseline model

A standard AR(1) model is generally used as a baseline model in the forecasting literature. This note investigates if a model can provide better predictions than the AR(1) baseline. If it cannot, then this would suggest that the more sophisticated modelling approaches do not provide much additional forecasting information than just looking at the past movements of NPLs themselves.

The general specification for an AR(1) model in first differences (quarterly percentage changes) is

$$\Delta NPL_{t+h} = \beta_0 + \beta_1 \Delta NPL_{t-1} + \varepsilon_t \qquad (1)$$

where h=0, 1, 2, 3 is the number of forecasted quarters ahead, NPL_t is the non-performing loan variable described above and ε_t is the error term that is normally distributed with a mean of zero and constant variance. β_0 and β_1 are the intercept and regression slope coefficients respectively.

b. Forecasting models

Bayesian VAR model

A Vector Autoregression (VAR) model, popularized by Sims (1980), is a type of multivariate time series model that describes the dynamic relationship among multiple variables over time in a systematic way. In a VAR model, each variable in the system is modelled as a linear combination of its past values and the past values of other variables in the system. This gives the benefit of allowing for the simultaneous consideration of the interdependencies among variables. VAR models are also flexible and do not impose strict assumptions about the underlying economic structure, making them widely applied for both forecasting and simulating the impact of structural economic shocks.

The general specification of a VAR model with two variables is

$$Y_t = \beta_{0,Y} + \beta_{Y1}Y_{t-1} + \ldots + \beta_{Y\rho}Y_{t-\rho} + \beta_{X1}X_{t-1} + \ldots + \beta_{X\rho}X_{t-\rho} + \varepsilon_t$$

$$X_t = \alpha_{0,X} + \alpha_{X1}X_{t-1} + \ldots + \alpha_{X\rho}X_{t-\rho} + \alpha_{Y1}Y_{t-1} + \ldots + \alpha_{Y\rho}Y_{t-\rho} + \nu_t.$$

In this equation:

- $\beta_{0,Y}$ and $\alpha_{0,X}$ represents the intercepts for variables Y_t and X_t respectively,
- β_{Yi} and α_{Xi} represent the coefficients of the lagged variables in the model,
- ε_t and ν_t represents the error term for variables Y_t and X_t at time t, where
- $\varepsilon_t \sim N(0, \sigma_\varepsilon)$ and $\nu_t \sim N(0, \sigma_\nu)$.

A Bayesian approach to estimating a VAR model is useful as this allows all variables of interest to be fed in with the relative importance of each variable determined using both the researcher's priors and the data. This reduces the risk of overfitting the model to improve its forecasting accuracy. In Bayesian VARs coefficients are assumed to have their own distribution as opposed to being simply estimated with OLS in a standard VAR. In this analysis Litterman-Minnesota priors are used, with a relatively tight hyper-parameter and lag specifications are chosen using the Schwarz information criterion (see Lutkepohl, 1993). The estimated VAR is then tested to ensure it is stable by confirming that all of its roots have a modulus less than one.

Time-varying parameter Bayesian VAR model

We also consider time varying parameter (TVP) Bayesian VARs (BVAR) to respond to potential non-linearity in the variables. TVP BVARs allow for coefficients in a linear BVAR model to vary over time following a specific law of motion, usually a random walk. They can also include stochastic volatility, which allows for time variation in the variances of the error term.[5] The relationship between NPLs and economic variables may be non-linear. For example, it is possible that NPLs tend to rise much faster when unemployment rises above a certain

[5] See Lubik & Matthes, (2015) and Haslbeck, Bringmann, & Waldorp (2021) for further details on estimating time varying BVAR models

threshold relative to its declines at the onset of a recovery in unemployment. This could be explained by borrowers quickly falling behind on lending repayments in the event of unemployment but if they later find another job then it may take time for them to catch back up on missed payments. The relationship between NPLs and house price growth may also contain some non-linearity. Sustained periods of negative house prices growth could matter more than sustained periods of positive growth as the borrower may be more inclined to default on their lending if they have no collateral relative to if they did. While TVP BVARs are still linear models they do provide a way to address non-linearities in the relationships.

Conditional forecasting with Bayesian VAR model

The final modelling approach used is producing forecasts of the future values of NPLs conditional upon assumed values of other variables. This approach, known as conditional forecasting, differs from those above which are not constructed conditional on a particular set of assumed values but rather are calculated iteratively using only information from within the system (Waggoner and Zha, 1993). In conditional forecasting the future trajectory of at least one of the variables in the VAR is treated as exogenous for forecasting purposes (see Chan, Pettenuzzo and Poon (2023) for an empirical example). It is plausible that producing conditioning forecasts gives a more accurate forecast for NPLs by incorporating additional information which these set of equations cannot incorporate. In this analysis the unemployment rate is conditioned on the projection presented in the most recently published *Monetary Policy Statement*. This form of conditioning can be termed 'hard conditioning' as the future paths of the conditioned variable are fixed rather than instead allowing the future values of the conditioned variables to lie within a certain range (soft conditioning). For simplicity, only the forecast of the unemployment rate is conditioned because the literature notes the theoretical and empirical relationship between unemployment and NPLs (see Foote et al., 2010 and Gyourko and Tracy, 2014).[6]

2. Forecasting methodology

Before discussing the details of our forecasting process, it is important to first introduce the terminology related to how the forecasting process is conducted. Pseudo out-of-sample forecasting is a statistical technique used to evaluate the predictive performance of a forecasting model. It involves estimating a model using a portion of the available data and then using the estimated model to generate predictions for periods that were not included in the estimation sample. This process is repeated for different forecast horizons to evaluate the model's ability to forecast over different time horizons. The term "pseudo" refers to the fact that the out-of-sample forecasts are not truly real time estimates as some of the data has been revised or updated since it was released. However, this technique can still help assess the generalizability of a forecasting model and its ability to make accurate predictions in new, unseen data. The basic steps involved in pseudo-out-of-sample forecasting are:

1. Divide the available data into an estimation sample and a holdout sample. The estimation sample is used to estimate the forecasting model, while the holdout sample is used to generate the pseudo-out-of-sample forecasts.

2. Estimate the forecasting model using the estimation sample.

[6] In addition, the eViews package required to do this needs the variable path to be inputted manually each time. A few models were tested with all variables conditioned except for the NPL but the results were not significantly different from only conditioning unemployment.

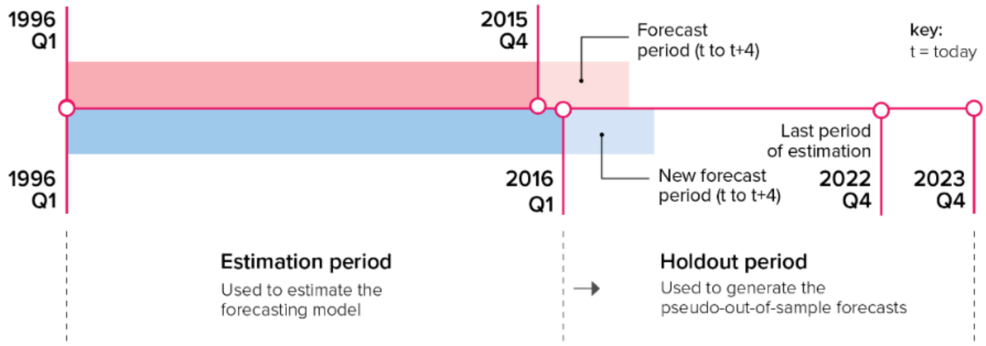
3. Generate forecasts for the holdout sample using the estimated model. This step involves feeding the holdout data into the estimated model and generating predictions for the subsequent periods.

4. Evaluate the accuracy of the forecasts using appropriate metrics, such as root mean squared error (RMSE).

5. Repeat steps 2-4 for different forecast horizons, using different portions of the available data for estimation and holdout.

Pseudo out-of-sample forecasting can be useful for comparing the predictive performance of different forecasting models and assessing the stability of a model's performance over time periods. However, it is important to note that the results of this technique may be influenced by the specific sample used for estimation and holdout, and care should be taken to ensure that the sample is representative of the population of interest. Pseudo out-of-sample forecast evaluation captures model specification uncertainty, model instability, estimation uncertainty, and the usual uncertainty of future events.[7] Pseudo out-of-sample forecasting attempts to simulate the experience of a real-time forecaster by performing all model specifications and estimation using data through date t, making an h-step ahead forecast for date t+h, then moving forward to date t+1 and repeating this through the sample. For this case, t is 1996 Q1 to 2015 Q4. The models are estimated across the sample 1996Q1 to 2015 Q4, giving out-of-sample forecasts for the t+h (h goes from 1 to 4). The models are estimated again, adding one quarter to the original sample for 1996 Q1 to 2016 Q1 and getting new forecasts for the t+h. This is done until 2022 Q4 to get the last forecasts for all forecast horizons up to h=4, i.e. 2023 Q1 to 2023 Q4. The model estimation for the forecasting procedure is recursive (using an expanding window, always starting with the same observation and adding one quarter at a time), rather than rolling estimation window of fixed length. Using a rolling window could better accommodate shifts in the underlying data-generating process if the sample size were longer. However, as this is a very short sample using a rolling window might cause an excess sensitivity to individual observations.

This pseudo out-of-sample forecasting process is illustrated below.



3. Forecast comparison

Finally, to measure forecasting performance, relative root mean squared errors (RRMSE) are used,

[7] See Stock and Watson (2008) for details.

$$RRMSE = \frac{RMSE\ AR(1)}{RMSE\ Model^x},$$

where $RMSE\ AR(1)$ is the root mean squared error (RMSE) from the forecasts of the baseline AR(1) model and $RMSE\ Model^x$ is the root mean squared error of each alternative model. RMSEs are calculated using the formula

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_{t+h} - y_{t+h})^2}{T}},$$

where $\hat{y}_{t+h}$ is the forecast of NPL by the relevant model, y_{t+h} is the actual NPL, and T is the number of replications (for the forecasting exercise). The $RRMSE$ represents the each model's ability to outperform the forecasts of the baseline AR(1) model.

In addition, in order to evaluate the forecasts, the methodology from Clark and West (2007) is used to test the statistical significance of the difference between the $RMSE\ AR(1)$ and $RMSE\ Model^x$. This test requires regressing the value

$$\widehat{CW}_{t+h} = (NPL_{t+h} - \widehat{NPL}_{A,t+h})^2 - [(NPL_{t+h} - \widehat{NPL}_{B,t+h})^2 - (\widehat{NPL}_{A,t+h} - \widehat{NPL}_{B,t+h})^2]$$

on to a constant and testing a null hypothesis that the out-of-sample RMSEs of the AR(1) model and the alternative model are the same. The hat denotes the forecast of NPL, and the sub-indices A and B represent the two models being compared (with A being the baseline AR(1) model and B denoting the model being compared). The null hypothesis is rejected if the corresponding t-statistic is significantly positive (one-sided test). Newey-West robust standard errors are used to assess the significance of the constant in this regression model.

6. Estimation results

This section presents the results of the forecast comparison. The previous section described the tools used to compare the forecasting performances of the models. Tables 2 presents the key results for each of the modelling approaches described above. Each model is compared to the baseline AR(1) model for forecasting NPLs. If the models have values greater than one and are significant (starred on the table), then this model has additional value at forecasting NPLs than a very simple autoregressive model.

Table 2: Relative root mean square errors of different forecasting models

Out of sample forecast analysis 2016Q1 – 2023Q4	h=1	h=2	h=3	h=4
BVAR	0.9040	0.9482	1.1154**	1.1077*
TVP-BVAR	0.7908	0.6027	0.3744	0.5070
Conditional BVAR	0.8351	0.8363	0.8993	0.8603

Starred numbers imply the model's forecasts are significantly more or less accurate than the baseline AR(1) model. * is significant at the 10% level, ** is significant at 5% level and *** is significant at 1% level. h is the number of quarters ahead of the forecast.

Overall, only the BVAR model tends to out-perform the simple AR(1) model at horizons of three and four quarters ahead. The other models are unable to forecast NPLs with significantly lower RMSEs than the baseline AR(1) model for this sample period. It is interesting that the BVAR performs better in the later horizons which is possibly explained by the role of macro-economic fundamentals becoming more important in the longer term.[8] At shorter horizons, it appears that non-performing loans are largely explained by the own past outturns, with macroeconomic conditions playing a more limited role.

Next, the models were tested from the end of 2019 onwards to determine if any model was able to better forecast the impacts of the COVID-19 pandemic on non-performing loans. Utilising the full sample period of data up until this point and conducting the iterative forecasts in the same manner as above, the results reveal a similar forecasting performance (shown in table 3). The BVAR model once again outperformed the baseline model in the later horizons, but the TVP-BVAR and conditional BVAR models were again generally unable to outperform the baseline AR(1) model.

Table 3: Relative root mean square errors of different forecasting models since COVID-19 pandemic

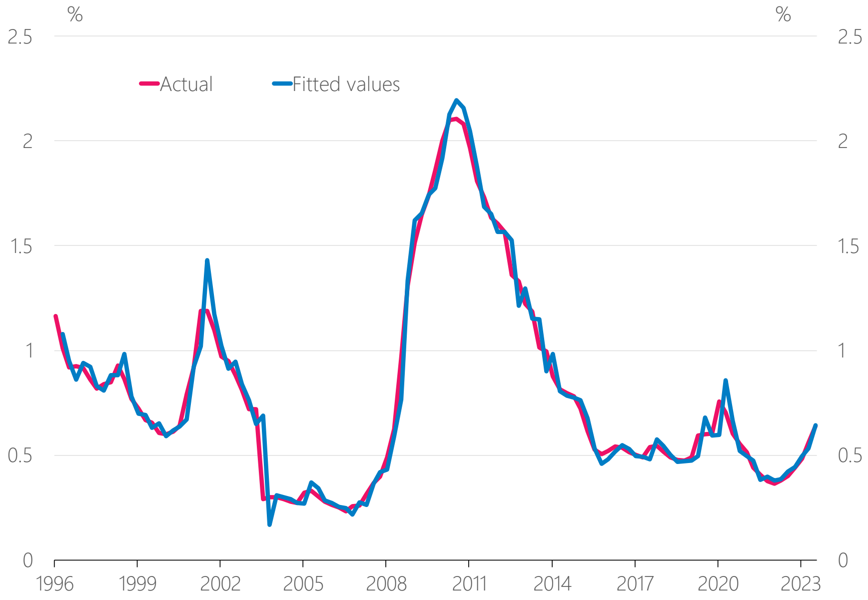
Out of sample forecast analysis 2020Q1 – 2023Q4	h=1	h=2	h=3	h=4
BVAR	0.7825	0.8593	1.5838***	1.4974**
TVP-BVAR	0.7510	0.5856	1.0129**	0.8187
Conditional BVAR	0.7115	0.7359	0.9572	0.9401

Starred numbers imply the model's forecasts are significantly more or less accurate than the baseline AR(1) model. * is significant at the 10% level, ** is significant at 5% level and *** is significant at 1% level. h is the number of quarters ahead of the forecast.

Overall, of all the models, the BVAR performs the best at out-of-sample forecasting compared to the simple baseline AR(1) model. This suggests there is value in considering macro-economic conditions when forecasting NPLs. This finding is notable given the relative lack of volatility within the NPL series. In the aftermath of the GFC, lending quality generally improved back towards its pre-GFC level and remained at such levels until the COVID-19 pandemic (figure 1). Even in aftermath of this unprecedented shock the impact on lending quality was fairly muted given the large monetary stimulus packages, government policies such as the 'wage subsidy' to support households and mitigations implemented by lenders, such as allowing borrowers to take mortgage repayment holidays. Simple models such as an AR(1) have an advantage in this environment because past lagged data tends to perform well at forecasting future data which is fairly stable. All of the models (including the baseline AR(1) forecasting model) have generally a good in-sample fit to the actual NPL series over time (illustrated for the best performing BVAR model in figure 3 below), further illustrating the low level of volatility and high persistence in this series. In addition to macroeconomic variables tested above, box A explores using higher frequency lending arrears data to forecast near-term non-performing loans.

[8] The forecast performance was unchanged when extending the horizon to eight quarters ahead and performing the same iterative forecasting exercise.

Figure 3: NPL forecasts from the Bayesian VAR



Box A: Forecasting NPLs with arrears data

Since 2017 the RBNZ has been collecting early-stage arrears data to capture the share of lending where a borrower has failed to make a payment (of principal and/or interest) when that payment was contractually due. This data is collected in three buckets, for lending that is:

- 30-59 days behind on a repayment/s but not impaired;
- 60-89 days behind on a repayment/s but not impaired; and
- 90 or more days behind on a repayment/s but not impaired.

These arrears data are captured alongside but are separate from impaired lending. Lending that is classified as in arrears is still ultimately expected to be fully repaid. For instance, lending with a missed repayment of 30 days but considered by the bank to be impaired (i.e. unlikely to be fully repaid) would be included in the impaired series rather than the 30 days past due. In this situation the lending would also be considered non-performing. Loans that are 30-89 days behind on payments are also sometimes referred to as delinquencies.

Borrowers who are facing significant budgetary constraints and financial distress may begin to miss successive payment obligations resulting in lending moving through these buckets as these borrowers fall further behind on their contracted repayments. At some point, banks may determine that these loans will not be fully repaid, and reclassify the loans as impaired, and include them in non-performing loans. Therefore, this information could be used to provide a near-term prediction of future non-performing lending.

To assess this, current non-performing loans are regressed on to 30-59 days arrears and 60-89 days arrears that are lagged by two and one month's respectively. Dummy variables are added for the 2020 COVID-19 lockdown periods in New Zealand (March 2020 – August 2020 and September 2020 – November 2020) when various support measures were enacted to support the domestic economy including mortgage 'holidays' and wage subsidies. This analysis is done for total lending, lending to the housing and business lending.

$$\Delta NPL_t = \beta_0 + \beta_1 \Delta 30 - 59\ days\ past_{t-2} + \beta_2 \Delta 60 - 89\ days\ past_{t-1} + \beta_3 \Delta COVID\ dummy_t + \varepsilon_t$$

Table A1 shows the RRMSE from these regressions for household lending. These results show arrears provide useful information in helping to forecast household NPLs. There was not a strong relationship between business lending arrears and business NPLs. This is likely because business lending arrears tends to be very 'lumpy' with medium and large sized businesses defaulting or making up on repayments resulting in significant changes in the aggregate series. Thus, the results could be heavily influenced by idiosyncratic factors.

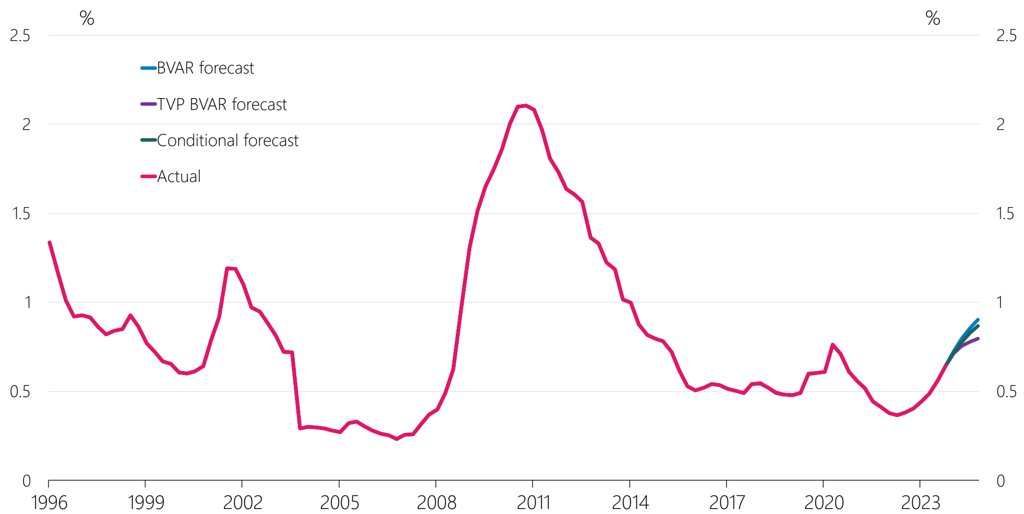
Out of sample forecast analysis 2022m1-2024m3	h=1
Housing	1.1181***

Starred numbers imply the model's forecasts are significantly more or less accurate than the baseline AR(1) model. * is significant at the 10% level, ** is significant at 5% level and *** is significant at 1% level. h is the number of quarters ahead of the forecast.

What do these models imply for future NPL growth?

In this section we use the models described above to assess the outlook for non-performing loans during the next 12 months. The recent economic environment has been relatively unique in New Zealand's history, with the aftermath of significant supply and demand shocks from the COVID-19 lockdowns, supply chain disruptions, conflict in Ukraine and the Middle East and significant net inward migration. While the OCR has reached its highest point in over a decade in response to inflation pressures, the unemployment rate has been slow to increase as the effects of monetary policy tightening have weigh on economic activity. Figure 4 shows the forecasts from the models with the Q1 2024 quarter of data as the starting point. Together these suggest NPLs could rise by a further 0.4 percentage points to 0.7-1 percent by the end of 2024. This would still be lower than the peak of NPL in the aftermath of the GFC, giving confidence that the New Zealand banking sector is in a strong position to weather the challenges on the horizon whilst continuing to support customers facing financial difficulties.

Figure 4: NPLs with one-year ahead forecast



Overall, bank lending quality has improved since the Global Financial Crisis (GFC), with business lending and high LVR residential mortgage lending comprising a smaller share of total bank lending. As a result, projected lending stress could be less severe than expected based on previous experiences of economic downturns. The recent period of high interest rates and low unemployment is unique in New Zealand in the last few decades and as a result the future of lending stress may differ from what historical relationships suggest. This means that forecasts of non-performing loans using models based on historical relationships have a high level of uncertainty (see Box B: Modelling NPLs in a high interest rate environment below for more information).

Box B: Modelling NPLs in a high interest rate environment

The combination of relatively high interest rates and low unemployment makes the current economic environment unique in recent NZ economic history. This suggests the pattern of future lending stress may differ to what is implied by historical relationships given these do not capture the impact of now significantly higher debt servicing costs. The analysis in this note has been undertaken over a period of a general trend downward in interest rates since the early 2000s which may present a modelling challenge.

During the 2022 solvency stress test New Zealand's largest four banks explored this issue in the context of higher interest rates. In this exercise, banks were required to conduct a sensitivity analysis of mortgage default rates to changes in interest rates, assuming all other parameters in the scenario were unchanged.[9] The estimates from this work provide an illustration of the direct impact of changes in interest rates to lending defaults, although it is important to note these results would be conditional on the economic environment in the period preceding the stress test.

Over the four-year stress test period, the level of defaults increases by approximately 30 percent when the mortgage rate increases from 4.5 to 7 percent. Defaults increase by 50 percent when the mortgage rate increases from 4.5 to 8 (figure B1). This indicates that as mortgage rates move higher, particularly above 7 percent, there is a non-linear increase in lending defaults. This non-linearity is consistent with the range of affordability test rates large banks have used since late 2020 to mid-2022 (mostly below 7 percent) to determine whether to lend to a mortgage applicant during this period (figure B2). Debt servicing strains are likely to become more acute as interest rates move above the original affordability test rates, which in this period were mostly below 7 percent.

Using this sensitivity analysis as an approximation for the expected increase in NPLs resulting from higher interest rates, then defaults should increase non-linearly as mortgage rates rise above 7 percent. This suggests that if mortgage rates rose by around another one percentage point from around where they are currently then defaults could increase by 20 percent. While this is an imperfect approach to modelling the relationship between economic conditions and

[9] For more information regarding the '2022 solvency stress test' refer to 2022 Bank Solvency Stress Test: Assessing the resilience of banks to a stagflation scenario - Reserve Bank of New Zealand - Te Pūtea Matua (rbnz.govt.nz)

NPL, it does provide a more complete estimate for the magnitude of increase in NPL which could arise in this economic environment.

Figure B1: Solvency stress test (SST) cumulative mortgage default rates

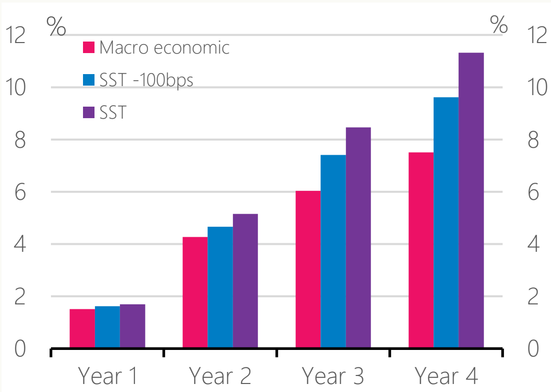
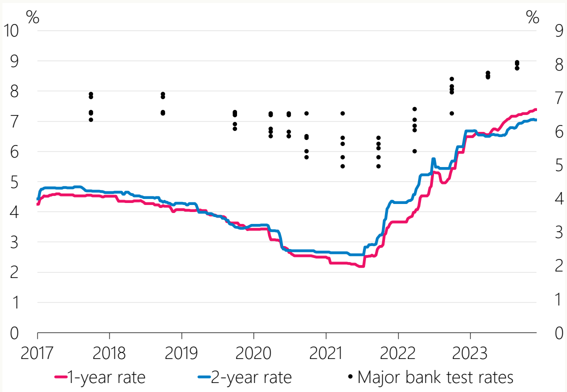


Figure B2: Mortgage rates and large five bank test rates



Note to figure B1: The macroeconomic bars show the default rates associated with no change in interest rates from the start of the scenario but everything else changing as laid out in the original scenario. SST -100bps shows the impact of the macroeconomic bars with interest rates changing by 100 basis points less than those outlined in the original scenario. The final set of bars labelled SST show the results from the full scenario (parameter for which are available here). The difference in the height of the blue and purple bars on this chart at year 4 shows the modelled impact of a one percentage point change in interest rates to defaults rates.

7. Conclusion

The ratio of non-performing lending to total lending is an important indicator for understanding the health of the financial system and specifically, how well borrowers are managing their debt obligations. Forecasting this provides a useful way to highlight potential upcoming challenges for lenders, which could create financial instability. This is an area of research that is relatively well developed within the literature for some other countries but so far has not been applied in a New Zealand context. Using similar modelling techniques to those utilized by other researchers this note finds these models are reasonably good at estimating NPLs with the BVAR model providing the best forecast performance. This suggests that there is value in utilising macro-economic conditions as a predictor of future changes in NPLs. This note also suggests we can leverage our existing data and analysis to explore the future path of NPLs. Data on lending arrears suggests this can be a good near-term predictor of housing NPLs, whilst sensitivity modelling from the 2022 solvency stress test suggests there may be non-linearity in the relationship between economic conditions and NPLs which is more prevalent as mortgage rates rise above affordability test rates.

References

Chan, J. C., Pettenuzzo, D., Poon, A., & Zhu, D. (2023). Conditional Forecasts in Large Bayesian VARs with Multiple Soft and Hard Constraints. *Available at SSRN 4358152*.

Dinh, M. T., Mullineux, A. W., & Muriu, P. (2012). Macroeconomic factors influencing UK household loan losses. *Journal of Financial Regulation and Compliance*, *20*(4), 385-401.

ECB. (21 December 2020). What are provisions and non-performing loan (NPL) coverage? What are provisions and non-performing loan (NPL) coverage? (europa.eu)

Erdas, M. L., & Ezanoglu, Z. (2022). How do bank-specific factors impact non-performing loans: Evidence from G20 countries. Journal of Central Banking Theory and Practice, 11(2), 97-122.

Foote, C., Gerardi, K., Goette, L., & Willen, P. (2010). Reducing foreclosures: No easy answers. *NBER Macroeconomics Annual*, *24*(1), 89-138.

Gyourko, J., & Tracy, J. (2014). Reconciling theory and empirics on the role of unemployment in mortgage default. *Journal of Urban Economics*, *80*, 87-96.

Haslbeck, J., Bringmann, L., & Waldorp, L., (2021). A Tutorial on Estimating Time-Varying Vector Autoregressive Models, Multivariate Behavioral Research, 56:1, 120-149, DOI: 10.1080/00273171.2020.1743630

Hunt, C. (2009). Banking Crises in New Zealand: An Historical Overview. *In RBNZ/VUW Professorial Fellowship Workshop, The global financial crisis: historical perspectives and implications for New Zealand, Wellington, June* (Vol. 17).

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012-1027.

Lubik, T. A., & Matthes, C. (2015). Time-varying parameter vector autoregressions: Specification, estimation, and an application. *Estimation, and an application*.

Lütkepohl, H. (1993). Testing for causation between two variables in higher-dimensional VAR models. In *Studies in applied econometrics* (pp. 75-91). Heidelberg: Physica-Verlag HD.

Mașcu, S., & PESCU, M. (2016, March). The impact of macroeconomic factors on non-performing loans in Romania: a time series analysis. In *International Finance and Banking Conference* (Vol. 231).

Reserve Bank of New Zealand. (2023). *Financial Stability Report November 2023.*

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Waggoner, D. F., and T. Zha (1999): Conditional forecasts in dynamic multivariate models. Review of Economics and Statistics, 81(4), 639–651.

Appendix

Table 1: Macroeconomic variables and their transformations

Variable	Transformation
Non-performing lending	Seasonally adjusted, monthly data that has been averaged to convert to quarterly frequency, difference from previous quarter.
Unemployment rate	Seasonally adjusted, difference from previous quarter.
CPI inflation	Difference from previous quarter.
House prices	Seasonally adjusted, difference from previous quarter.
Floating mortgage rate	Monthly data that has been averaged to convert to quarterly frequency, difference from previous quarter.
Official cash rate	Quarterly average of the OCR, difference from previous quarter.
Household credit	Monthly data that has been averaged to convert to quarterly frequency, difference from previous quarter.
Output gap	Published in each MPS based upon output gap indicator suite of models, difference from previous quarter.
Trade weighted NZD index	Quarterly average of the TWI, difference from previous quarter.
Mortgaged household debt servicing ratio	Average interest servicing costs as a share of mortgaged households' disposable incomes. Also published in the May 2023 Financial Stability Report.