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A Meta-Learning Model of Philippine Bank Lending Behaviour*

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This study develops a meta-learning framework to predict the lending behaviour of Philippine commercial banks using aggregate bank financial ratios and macroeconomic variables. Five baseline machine learning models – Boosting, k-Nearest Neighbours, Neural Networks, Random Forest, and Support Vector Machine – were employed, with their outputs synthesised through LASSO-regularised regression. Results demonstrate that the metamodel consistently achieves superior accuracy, lower error levels, and closer proximity to perceived bank lending behaviour. Robustness checks confirmed stability across volatile and low-variance regimes using Ridge and Elastic Net, while feature importance highlighted profitability and asset quality as key drivers of lending behaviour.

Journal of Economic Literature (JEL) codes: C45, E58, G21

Keywords: machine learning, metamodeling, bank lending behaviour

1. Introduction

Bank lending behaviour shapes economic activity, financial stability, and the transmission of monetary policy. Lending decisions by banks directly influence the availability of credit to households and firms, thereby affecting investment, consumption, and overall economic growth (*Anyanwu et al. 2017*). In emerging economies such as the Philippines, where banking institutions serve as the primary channel of financial intermediation, understanding the determinants of lending behaviour is essential for regulators, policymakers, and market participants.

Traditional analyses of lending behaviour often rely on linear econometric models that assume stable relationships between bank-specific indicators and

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macroeconomic variables. However, empirical evidence suggests that lending outcomes are shaped by complex, nonlinear interactions that vary across economic cycles and institutional contexts (*Dou et al. 2023*). These limitations have prompted growing interest in machine learning techniques, which can uncover hidden patterns and improve predictive accuracy in financial systems (*Adegbite 2024; Olowe et al. 2024*).

Recent studies have applied machine learning to diverse banking challenges, including credit risk assessment, fraud detection, and non-performing loan prediction (*Hashemi et al. 2023; Muslim et al. 2023*). Yet, few have focused on forecasting lending behaviour itself, despite its representation of the banking system's collective stance of credit standards and its centrality to monetary policy transmission and systemic stability. Moreover, reliance on single-model approaches often results in overshooting, lagging, or miscalibrated forecasts, reflecting the inherent uncertainty of financial data-generating processes (*Wu – Levinson 2021*). Given these limitations, this study sought to answer two main questions, (i) *Can a meta-learning model outperform benchmark and individual machine learning models in predicting bank lending behaviour?* (ii) *Which bank-specific and macroeconomic indicators are most influential in predicting bank lending behaviour?*

The questions are addressed by developing a two-layered meta-learning framework that integrates multiple machine learning models – Boosting, k-Nearest Neighbours, Neural Networks, Random Forest, and Support Vector Machine – into a unified and regularised metamodel. Using quarterly data from 2009 to 2024, the framework captures both aggregate bank financial ratios (e.g. capital adequacy, asset quality, profitability) and macroeconomic variables (e.g. GDP growth, inflation, policy rates). Synthesising the strengths of individual learners enables the metamodel to deliver more robust and accurate forecasts of lending behaviour, particularly during periods of volatility such as the COVID-19 pandemic.

The contribution of this paper is threefold. First, it introduces a novel application of meta-learning to predict lending behaviour in the Philippine banking sector. Second, it demonstrates the resilience and superiority of the metamodel over single-model approaches in capturing structural breaks and regime shifts. Third, it provides practical insights for regulators and policymakers by identifying the most influential drivers of lending behaviour, thereby supporting more effective monitoring of systemic risk and monetary policy transmission.

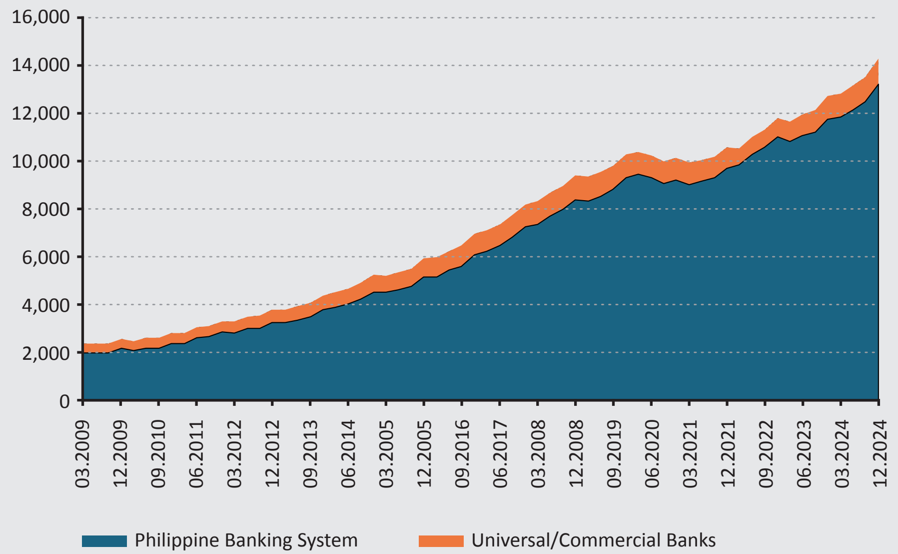
2. Related works

2.1. The Philippine banking industry

The Philippine banking system serves as the backbone of financial intermediation. It is characterised by four primary groups, each serving distinct functions. As of 2024, a total of 44 universal and commercial banks dominate the industry's total assets (27.4 trillion pesos) at 93.8 per cent (*Bangko Sentral ng Pilipinas 2025a*). These banks primarily offer full-service banking, investment services, and large corporate lending. There are also 41 thrift banks focusing on retail, consumer credit, and housing loans; 383 rural and cooperative banks focusing on community-based lending primarily for agricultural and micro- and small-sized enterprises; and six digital banks that offer end-to-end banking through digital platforms without physical branches.

Lending activity is one of the primary functions of banks. The total loan portfolio of the system amounted to approximately at 14.3 trillion pesos in 2024. The distribution of these loans is mainly dominated by universal and commercial banks, which account for 92.3 per cent. *Figure 1* shows the loan portfolios of the Philippine banking system and of the universal and commercial banks, showing a stable uptrend over the years.

Figure 1
Total loan portfolio of the Philippine banking system and universal/commercial banks (2009–2024)



Note: Values in billions of Philippine pesos.

Source: Bangko Sentral ng Pilipinas' (2025a) report on Philippine banking system

2.2. Machine learning and metamodeling

One central challenge in forecasting is model uncertainty. Traditional approaches often assume the existence of a true model that can fully describe the data-generating process. However, empirical evidence shows that single models frequently underperform as they fail to capture the actual complexity and variability inherent in real-world financial systems. *Siegert et al.* (*2016*) stated that ignoring model uncertainty results in biased parameter estimates and overly narrow prediction intervals, leading to inaccurate forecasts. Moreover, *Makridakis and Bakas* (*2016*) found that accurately propagating uncertainty about the model structure is often overlooked, which can lead to overconfident predictions and insufficient hedging against uncertainties.

The limitations of a single-model prediction have driven this study's interest in employing a meta-learning approach. *Lin et al.* (*2019*) suggested a combination of multiple models to improve forecasting reliability and address model uncertainty. *Wu and Levinson* (*2021*) noted that reliance on a single model often underperforms and is more prone to erroneous results, whereas combining single models offsets each of their weaknesses within, producing more accurate and less erroneous results. This is also proven by *Rane et al.* (*2024*) wherein they showed that combining forecast techniques outperforms individual models when accuracy and diversity are balanced. Building on this, *Montero-Manso et al.* (*2020*) introduced meta-learning algorithms that automatically select and weigh forecasts, demonstrating that averages surpass both simple combinations and the best single models. These advances address the challenge of identifying optimal weights without bias or instability.

In addition, meta-learning allows for small and limited data as it inherently acquires and improves on the initial parameters from other models. This learning-to-learn approach was shown to adapt better on minimal data. For instance, it can produce personalised recommendations for new users of e-commerce despite limited interaction history (*Naser 2026*). Also, *Safonova et al.* (*2023*) mentioned that problems with small sample size can be addressed through ten techniques. Those include combining individual models that learned differently and training the models several times to reduce biases and over-optimistic performance. Moreover, to avoid overfitting, regularisation approaches through least absolute shrinkage and selection operator (LASSO), Ridge, or Elastic Net, allows maximisation of information even for small datasets (*Naser 2026*). Hence, this study considered an expanding window scheme and two-layer meta-learning through regularisation to account for few observations.

Existing banking studies using the integration of machine learning techniques through a metamodel showed significant results in addressing challenges such as credit risk and operational efficiency. *Kavirathne et al.* (*2022*) developed a meta-learning model to predict non-performing loans in Sri Lankan financial institutions, achieving high accuracy and demonstrating effectiveness in managing credit risk. Moreover, *Savolainen and Collan* (*2020*) showed how metamodels reduce the complexity and computational demand of simulations in investments, allowing faster and effective risk analyses. *Paz et al.* (*2025*) supported this using optimisation techniques for feature selection in credit risk assessment, enhancing the robustness and efficiency of machine learning models.

2.3. Machine learning applications in banking

Machine learning has been widely applied in the banking sector, particularly in risk management and fraud detection. *Donepudi* (*2017*) and *Olowe et al.* (*2024*) stated that the integration of advanced machine learning techniques not only enhances efficiency but also improves decision-making and customer experience in banking operations. *Leo et al.* (*2019*) found that these techniques are being utilised to better manage various banking risks, such as credit, market, operational, and liquidity risks. *Guerra and Castelli* (*2021*) found that these also apply to bank stress testing, showing promise in developing early warning systems for bankruptcy. *Hashemi et al.* (*2023*), on the other hand, employed machine learning to improve the detection of fraudulent transactions, achieving high performance metrics. In terms of lending behaviour, machine learning is being used to enhance credit risk assessment and improve loan approvals as it has shown significant effectiveness in predicting loan defaults and assessing creditworthiness (*Anand et al. 2022; Chen 2022*).

Based on the existing literature, *Leo et al.* (*2019*) stated that the usability of machine learning still requires exploration in future research. Hence, this study used machine learning for a different approach: to predict the lending behaviour of commercial banks in the Philippines using aggregate bank financial ratios and macroeconomic variables as features. *Abdolshah et al.* (*2020*) found that macroeconomic shocks influence banks' lending based on risk profile. Also, *Yitayaw* (*2021*) revealed that capital adequacy enhances lending while macroeconomic shocks can have adverse effects. *Ahmed et al.* (*2021*) showed that non-performing loans are a result of lending activities as influenced by gross domestic product growth.

2.4. Bank lending behaviour and its predictors

The systematic monitoring and analysis of bank lending behaviour, particularly in terms of tightening or easing credit standards, is imperative for several reasons. First, lending standards directly influence the availability and cost of financing for businesses and households, thereby shaping investment decisions, consumption patterns, and overall economic activity (*Anyanwu et al. 2017; Bernanke 2018*). When banks tighten credit standards, access to financing becomes restricted, limiting opportunities for growth and expansion. Conversely, easing credit standards increases access to funds, stimulating borrowing and investment. Second, understanding changes in lending behaviour enables central banks and regulators to evaluate the effectiveness of monetary policy transmission. For example, if adjustments in interest rates do not correspond to changes in credit standards, the intended impact of monetary policy on the real economy may be muted or ineffective (*Aikman et al. 2016; Fung et al. 2000*). Third, the drivers of credit standards provide valuable insights into potential vulnerabilities within the banking system. Identifying these drivers allows policymakers to design interventions that mitigate systemic risks and prevent financial crises (*Bernanke 2018; Claessens – Kodres 2014*). Moreover, quantifying the influence of economic and bank-specific factors on lending adjustments is essential for addressing underlying issues during periods of excessive tightening or easing (*Ahmed et al. 2021; Bassett et al. 2014*).

Existing research highlights the significant role of macroeconomic indicators in shaping lending behaviour. Inflation, for instance, has been consistently linked to tighter credit standards. *Rostagno et al.* (*2021*) found that central bank interventions aimed at controlling inflation often reduce credit supply, as banks respond to stricter monetary policies by adopting more cautious lending practices. *Ashraf* (*2021*) and *Nguyen et al.* (*2025*) further emphasised that high inflation generates uncertainty for banks, particularly regarding repayment risks, leading to stricter loan covenants and collateral requirements. By contrast, strong GDP growth rates are generally associated with an easing of credit standards. *Naili and Lahrichi* (*2020*) and *Yurdakul* (*2014*) demonstrated that favourable macroeconomic conditions reduce perceived credit risk, encouraging banks to extend more loans. This behaviour reflects the improved repayment capacity of borrowers in a growing economy, which incentivises banks to ease lending terms and expand credit lines.

Beyond macroeconomic conditions, bank financial ratios also play a critical role in determining lending behaviour. Capital adequacy, for example, has been shown to enhance a bank's capacity to lend. *Madugu et al.* (*2020*) and *Olawale* (*2024*) revealed that higher capital adequacy ratios allow banks to maintain or even ease credit standards across different economic cycles. *Kozak* (*2021*) similarly argued that well-capitalised banks are more resilient and possess greater capacity to absorb shocks, enabling them to adopt more flexible credit policies. Asset quality, measured through the past due ratio, is another important determinant. *Schiantarelli et al.* (*2016*) concluded that increases in non-performing loans prompt banks to adopt more cautious lending policies to safeguard liquidity and prevent further losses. *Naili and Lahrichi* (*2020*) added that past due ratios reflect not only the performance of a bank's existing borrowers but also broader industry conditions, making them a reliable indicator of heightened credit risk.

Profitability measures such as return on assets and return on equity are also closely associated with lending behaviour. *Miglo* (*2018*) and *Parker* (*2002*) reported that higher profitability increases a bank's risk-bearing capacity, incentivising it to expand lending through more lenient credit standards. Profitable banks are better positioned to attract borrowers by offering favourable terms, thereby increasing lending volumes. *Bancel and Mittoo* (*2011*) further noted that profitability enhances financial flexibility, allowing banks to sustain high lending activity even during periods of economic uncertainty. Hence, the importance of profitability as a driver of credit expansion reflects its role in shaping banks' willingness to ease lending standards.

Figure 2
Research model

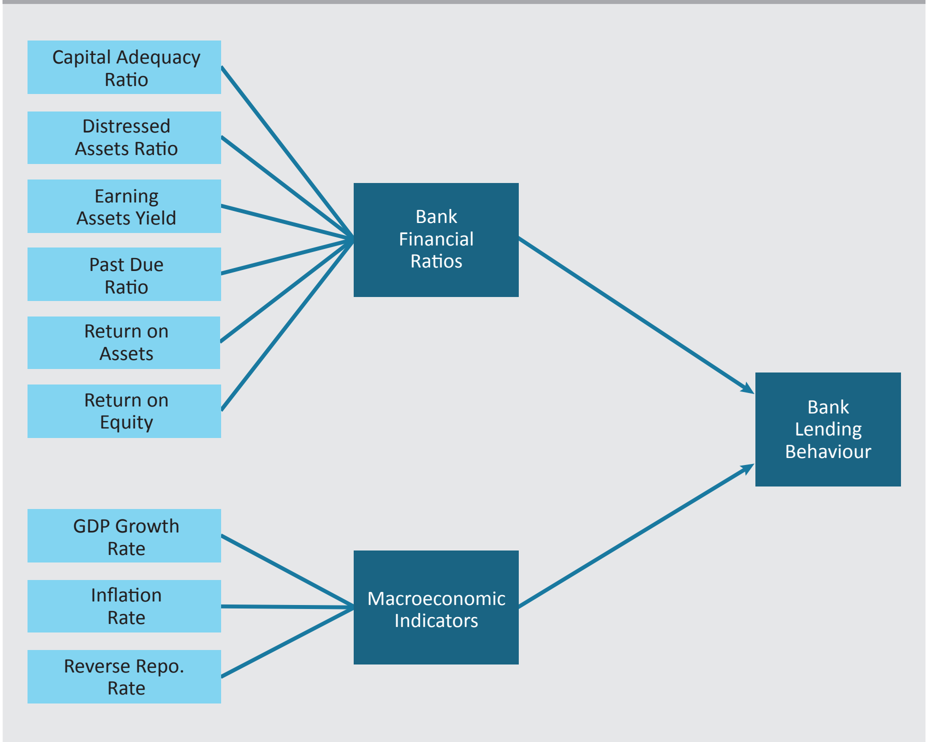


Figure 2 illustrates the research framework linking bank-specific financial indicators and macroeconomic conditions to the lending behaviour of Philippine commercial banks. The model emphasises how internal measures of financial health interact with external economic forces to shape lending decisions.

3. Methods

3.1. Data description and sources

This study utilised quarterly data covering the period 2009–2024, retrieved from the Bangko Sentral ng Pilipinas (BSP). The objective is to predict bank lending behaviour using a combination of aggregate bank financial ratios and macroeconomic variables. The target variable is the BSP Senior Bank Loan Officers' Survey (SLOS) diffusion index capturing the tightening or easing of credit standards. The survey provides collective perceptions of banks in managing their corporate and household loans – the willingness to extend credit – under the prevailing conditions.

Table 1
Descriptive statistics of features and target for first-layer learners (2009–2024, n=64)

Variable	Unit	Min	Mean	SD	Median	Max	r
Bank Lending Behaviour	%	–9.700	11.461	13.790	9.900	65.200	–
Capital Adequacy Ratio	%	15.000	16.656	0.954	16.500	19.200	–0.265
Distressed Assets Ratio	%	2.200	5.106	2.038	5.150	9.800	0.170
Earning Assets Yield	%	3.800	4.706	0.821	4.550	6.800	–0.335
GDP Growth Rate	%	–15.000	7.848	5.201	9.000	15.200	–0.523
Inflation Rate	%	–0.200	3.509	1.770	3.300	8.700	0.209
Past Due Ratio	%	1.500	3.072	1.010	3.300	4.700	0.362
Return on Assets	%	0.800	1.305	0.256	1.300	2.000	–0.537
Return on Equity	%	6.500	10.877	1.939	10.550	15.800	–0.535
Reverse Repurchase Rate	%	2.000	3.938	1.215	4.000	6.500	–0.105

Note: SD – standard deviation. Positive correlations (r) are expected to tighten while negative correlations are expected to ease credit standards.

As shown in *Table 1*, the positive and negative correlation values indicate the relationships of features with bank lending behaviour. Positive correlation means a tightening of credit standards, while negative correlation means an easing of such. Based on the results, increases in distressed assets, loan delinquencies, and inflation are associated with tightening. Conversely, higher capital adequacy, profitability, and reverse repurchase rate are associated with easing.

3.1.1. Bank lending behaviour

The SLOS diffusion index is a net measure of tightening versus easing lending responses, computed as the proportion of banks reporting tightening minus the proportion reporting easing. A positive net index indicates that more banks have tightened credits standards than those that eased, while a negative net index indicates the opposite. Because the index is a direct survey-based measure, it is treated as an operational proxy for banks' collective lending stance to both bank financial metrics and external economic pressures. The SLOS only covers universal and commercial banks.

3.1.2. Aggregate bank financial ratios

The aggregate bank financial ratios provide an estimate of how the financial health of banks influences their lending behaviour. These ratios are calculated as averages of the total number of universal and commercial banks in the Philippines. Ratios from other types of banks, such as thrift, cooperative, and rural banks, were excluded from this analysis because they are not respondents of the SLOS. While individual bank-level data can offer specific insights, this paper utilises aggregate financial ratios because of two reasons. First, the target variable in this study is the SLOS diffusion index of bank lending behaviour. Since the SLOS diffusion index captures collective perceptions of the entire universal and commercial banking industry, the predictors must be measured at the same level of aggregation to ensure consistency. Second, individual banks may exhibit outlier behaviour due to specific corporate strategies, mergers, or localised shocks that do not reflect the broader industry trend. Aggregation smooths these fluctuations, allowing the predictive models to focus on the systematic drivers of credit standards.

The capital adequacy ratio measures the sufficiency of a bank's capital relative to its risk-weighted assets. Its consistently high mean and low variability indicate sustained capital strength and lending capacity throughout the covered periods. Asset quality is captured through distressed assets and past due ratios. The distressed assets ratio represents the proportion of non-performing and restructured assets, and serves as a proxy for credit risk. The past due ratio measures delinquency levels, with higher values signalling elevated credit risk and reduced willingness to extend loans. Both indicators show fluctuations over time, suggesting shifts in the risk environment faced by banks. Profitability contributes an additional dimension to the analysis. Return on equity reflects shareholder profitability, while return on assets evaluates profitability relative to total assets. Both highlight operational efficiency. Earning assets yield measures the return generated from productive assets and provides insight into how asset performance affects lending incentives.

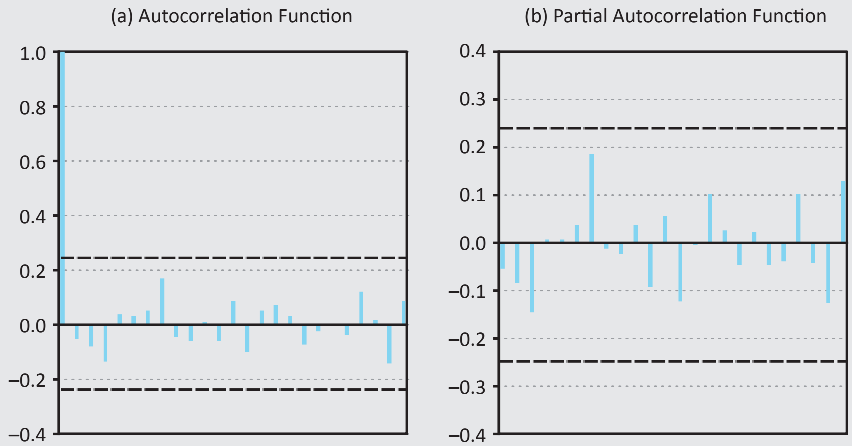
3.1.3. Macroeconomic indicators

The macroeconomic indicators contextualise the broader environment in which banks make lending decisions. The GDP growth rate represents overall economic activity, and higher growth generally supports increased credit demand. It is the most volatile predictor in the dataset, with an average value close to its standard deviation, indicating exposure to significant economic shocks across the covered period. The inflation rate captures price stability and affects real returns as well as banks' perceptions of lending risk. The reverse repurchase rate serves as the BSP's primary monetary policy instrument and directly influences funding costs, liquidity conditions, and the overall credit environment. Movements in both inflation and policy rates reflect active monetary adjustments and changing macroeconomic conditions that shape the lending behaviour of commercial banks.

3.2. Data preprocessing and model training

The dataset contains no missing observations. It was transformed to improve the performance of the benchmark and first-layer machine learning models. The target and input variables are adjusted and individually assessed if they are stationary. Non-stationarity persisted using only the raw data. After applying first-order difference (d = 1), stationarity was achieved as evidenced by *Figure 3* on bank lending behaviour, where lags fell within the 95-per cent confidence interval. This is further supported by the results of the Augmented Dickey–Fuller (ADF) test, $t(3) = -5.240$, $p < 0.01$, and Phillips-Perron (PP) test, $Z_{\rho} = -58.266$, $p < 0.01$, which both show significance of less than 0.05.

Figure 3
Autocorrelation and partial autocorrelation of bank lending behaviour after first-order differencing



Note: Lambda = 1, d = 1, D = 0, CI = 0.95, CI type = white.

Furthermore, the study employed a one-quarter-ahead out-of-sample prediction design to eliminate look-ahead bias. The target variable is being predicted using bank-specific and macroeconomic features lagged by one quarter (t–1). The lagged specification shows that the results are a true out-of-sample forecast, providing a multi-month lead time for policymakers before actual data is published.

3.2.1. Benchmark models

Prior to the implementation of the meta-learning framework, this paper established minimum-performance references. These benchmarks are frequently used by central banks when evaluating more complex approaches. The first benchmark model is a Random Walk (RW) with drift (0,1,0). This univariate model was selected based on the results of ADF and PP tests. In addition, two types of Autoregressive Integrated Moving Average (ARIMA) models were implemented. A non-seasonal ARIMA utilises three autoregressive terms and one moving average (3,1,1) to capture short-term dependencies in lending behaviour. Also, a seasonal ARIMA (SARIMA) was optimised through backward testing of the Akaike Information Criterion. It incorporated seasonal strand $(1,0,1)_s$ to account for periodic cycles identified during the diagnostic phase. The diagnostic integrity of these benchmark models was verified by ensuring that the residuals followed a normal distribution and functioned as random white noise.

3.2.2. First-layer machine learning models

Then, five first-layer machine learners were employed to generate first-layer predictions prior to the construction of the metamodel (MTM). Each algorithm offers a distinct methodological bias, enabling the metamodel to leverage diverse prediction patterns.

Although the benchmark ARIMA models utilise an autoregressive component, this paper did not consider including the lagged values of SLOS diffusion index in the feature set. This decision directly aligns with addressing the research question of which bank-specific and macroeconomic indicators are most influential in predicting bank lending behaviour. Additionally, it mitigates the swamping effect and maintains the predictive capacity of the existing features. Including the lagged SLOS diffusion index would distort the feature importance scores (feature masking), making it difficult to see which indicators are truly influential. Consequently, the baseline learners are forced to extract predictive signals solely from the indicators, providing policymakers with more actionable insights into the underlying causes of lending behaviour rather than relying on the trend persistence of the SLOS diffusion index. Nonetheless, the comparison remains technically robust as all models adhere to same chronological constraint, wherein all inputs are restricted to the data available prior to the quarter being predicted.

Boosting regression (BST) was included for its ability to iteratively reduce bias by correcting residual errors in decision tree ensembles. This makes BST responsive to nonlinearities and local structural changes in the data, such as shifts in credit standards during different economic periods. As shown in *Equation* (*1*), the model was trained using a shrinkage parameter (v) of 0.1, an interaction depth of 1.0, a minimum of ten observations per terminal node, and 100 trees (M) with 50-per cent sampling under a Gaussian loss function. The $h_m(x_{t-1})$ contains individual weak learners that is iteratively added to correct the errors of previous ones. As the training window expands, the shrinkage parameter was decreased down to 0.01 and the interaction depth was increased up to 2.0 so the model can safely learn with the increasing information without overfitting to the early smaller samples.

$$\hat{y}_t^{BST} = \sum_{m=1}^{M} v\, h_m(x_{t-1}) \tag{1}$$

k-nearest neighbours (KNN) regression was employed as a simple, non-parametric learner that predicts values based on the most similar past observations. This allows it to identify localised patterns in lending behaviour, providing a flexible way to explain variance through local neighbourhood structures. The model was trained with rectangular weights and Euclidean distance, optimised from six to eight nearest neighbours (k) depending on the number of observations in the training set. This is necessary as the density of neighbourhoods increases along with the expanding window. The $N_k(x_{t-1})$ is the set of indices of the k nearest neighbours to x_{t-1}, as shown in *Equation* (*2*).

$$\hat{y}_t^{KNN} = \frac{1}{k} \sum_{i \in N_k(x_{t-1})} y_i \tag{2}$$

Neural networks regression (NNR) was applied to model high-dimensional interactions and identify latent structures within the interplay of bank financial ratios and macroeconomic variables. It provides an adaptive framework for modelling dynamic patterns inherent in the financial sector. The NNR was trained using a rectified linear activation function (Ø), a maximum of 100,000 repetitions, and a topology optimised through a genetic-algorithm procedure that scaled within the expanding window size. This procedure searched a population size of 20, evolving from a shallow architecture of one hidden layer in early windows up to three layers and ten nodes per layer. The w represents the weights and b represents the optimised biases, as shown in *Equation* (*3*). Parent selection followed a roulette wheel approach with 10-per cent mutation probability and 10-per cent fitness-based survival.

$$\hat{y}_t^{NNR} = \sigma\left(\sum_{j=1}^{H} w_j \bullet \emptyset\left(\sum_{i=1}^{D} w_{ij} x_{i,t-1} + b_i\right) + b_j\right) \tag{3}$$

Random forest regression (RFR) was selected for its robustness and variance-reduction properties. By averaging predictions across multiple decorrelated decision trees, it provides a reliable baseline that mitigates the risk of overfitting; which is a common issue when dealing with the inherent uncertainty of data. As shown in *Equation* (*4*), the model was trained with 50-per cent coverage per tree across an ensemble of 100 trees. B is the total number of trees and $T_b(x_{t-1})$ is the prediction of a single tree.

$$\hat{y}_t^{RFR} = \frac{1}{B}\sum_{b=1}^{B} T_b(x_{t-1}) \tag{4}$$

Support vector machine regression (SVM) was employed for its margin maximisation and effectiveness in high-dimensional contexts. It offers a structured approach to regression, which is useful for maintaining accuracy even when the feature space is complex. It was trained with linear weights, a termination tolerance of 0.001, an insensitive-loss function of 0.01, and a violation cost of up to five, which was adjusted upward as the expanding window provides more evidence. As shown in *Equation* (*5*), the α_i–α_i* are Lagrange multipliers and $<x_i, x_{t-1}>$ is the inner product of the feature vectors.

$$\hat{y}_t^{SVM} = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\langle x_i, x_{t-1}\rangle + b \tag{5}$$

In *Equation* (*6*), all baseline learners estimate a prediction function where x_{t-1} includes both lagged bank-specific indicators and macroeconomic variables. Although each algorithm approximates f(.) differently, they all share the same equation as:

$$\hat{y}_t = f(x_{t-1}) + \epsilon_t, \qquad x_{t-1} = [CAR_{t-1}, DAR_{t-1}, EAY_{t-1}, \ldots] \tag{6}$$

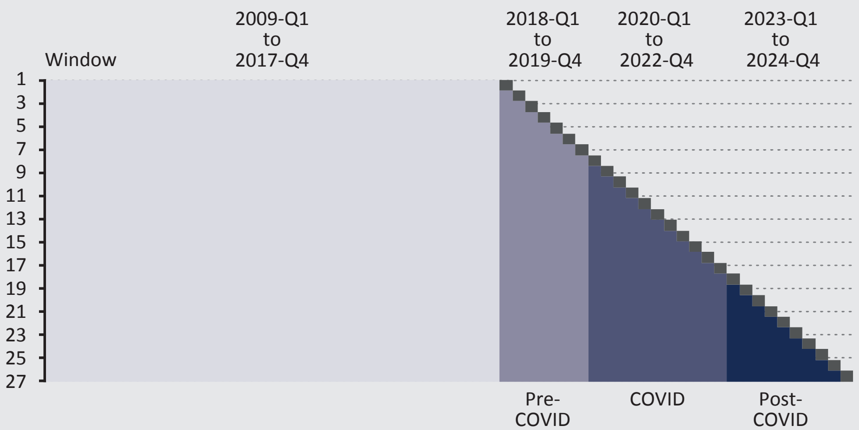
All out-of-sample predictions, both for benchmark and first-layer learners, were converted back from first-order differenced values to the original scale. Together, these baseline learners produce prediction patterns essential for the meta-learning strategy of this study. Their complementary strengths and weaknesses provide the diversity of signals that the metamodel synthesises into a more accurate and stable forecast of bank lending behaviour.

3.3. Expanding window protocol

The benchmark and machine learning models are trained under a strictly chronological expanding-window protocol. The dataset covering 16 years from 2009 to 2024 is divided into training and test subsets without shuffling. Given a total of only 64 quarterly observations per variable, this study addresses problems with small and limited data through expanding window, meta-learning, and regularisation, as recommended by *Naser* (*2026*) and *Safonova et al.* (*2023*).

As shown in *Figure 4*, the first training window covers the actual data of both the feature and target variables from the first quarter of 2009 to the last quarter of 2017, representing an initial training ratio of about 56.25 per cent of the sample. Then, the succeeding test subsets were added with additional quarters until the third quarter of 2024. The entire process produced a total of 28 one-quarter-ahead out-of-sample predictions.

Figure 4
Expanding window process



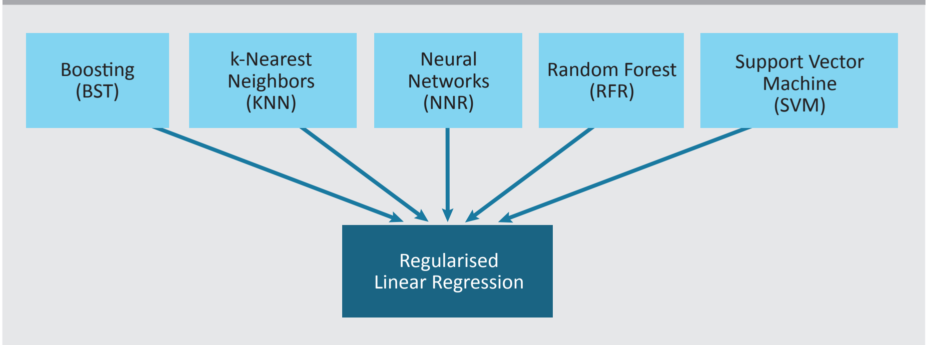
Note: Lighter to darker shades are covered periods of training windows, while the black shades are out-of-sample predictions.

The out-of-sample predictions under this protocol covers three window frames. The first frame covered one-quarter-ahead predictions of a pre-COVID condition from the first quarter of 2018 to the last quarter of 2019, totalling eight quarter predictions. Then, the models continued to expand the training coverage to produce similar predictions during the pandemic (2020-Q1–2022-Q4, 12 quarter predictions) until the post-pandemic frames (2023-Q1 to 2024-Q4, eight quarter predictions).

3.4. Metamodeling framework

A two-level metamodel architecture as shown in *Figure 5* is implemented to predict lending behaviour of banks in the Philippines. In the first layer, all models at every step of the expanding window process are refitted using only the data available up to the quarter immediately before the one being predicted (*t*–1). Each model then produces a single-quarter-ahead out-of-sample prediction as discussed in the protocol. The hyperparameters are tuned only within the data available in each training windows to prevent exposure to look-ahead bias.

Figure 5
Metamodel architecture



This study acknowledges that each first-layer learner exhibits different strengths. BST emphasises error correction, KNN leverages local similarity, NNR capture high dimensional patterns, RFR provides stability through averaging, and SVM applies margin-based regression. Hence, combining their strengths reduces overall variance and improves predictive capacity. To do so, the first-layer predictions are passed to a meta-learner in the second level using regularised linear regression with a LASSO penalty. It serves as the primary specification for three practical reasons: (1) LASSO can zero-weight base learners that contribute little, (2) it shrinks and selects base learners to mitigate weight instability and reduce overfitting under small samples, and (3) it tempers the tendency to overreact to idiosyncratic patterns in any one learner, which is valuable around structural breaks such as the COVID-19 spikes.

The regression equation for a metal-learner can be shown as:

$$\begin{aligned}\hat{y}_t^{MTM} = {} & \alpha + \beta_1 \hat{y}_t^{BST}(x_{t-1}) + \beta_2 \hat{y}_t^{KNN}(x_{t-1}) \\ & + \beta_3 \hat{y}_t^{NNR}(x_{t-1}) + \beta_4 \hat{y}_t^{RFR}(x_{t-1}) + \beta_5 \hat{y}_t^{SVM}(x_{t-1}) + \epsilon_t\end{aligned} \tag{7}$$

With LASSO penalty:

$$\frac{min}{\beta}\left\{\sum_{t=1}^{n}(y_t - \hat{y}_t^{MTM}(x_{t-1}))^2 + \lambda \sum_{j=1}^{5}\left|\beta_j\right|\right\} \tag{8}$$

To demonstrate that the results are not an artifact of the LASSO penalty, this paper implemented two alternative meta-learners: Ridge and Elastic Net. Ridge provides stable shrinkage when predictors are strongly collinear but retains all learners with small positive weights, while Elastic Net blends the sparsity of LASSO with the grouping stability of Ridge. The regularisation strengths, including the Elastic Net mixing parameter, were selected through the same expanding-window used for the first-layer out-of-sample construction, ensuring no future data informs the tuning process. Equation for regularized regression with Ridge penalty:

$$\frac{min}{\beta}\left\{\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t^{MTM}(x_{t-1}))^2+\lambda\sum_{j=1}^{5}\left|\beta_j^2\right|\right\} \tag{9}$$

While for regularized regression with Elastic Net penalty:

$$\frac{min}{\beta}\left[\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t^{MTM}(x_{t-1}))^2+\lambda\left(\frac{1-\alpha}{2}\sum_{j=1}^{5}\beta_j^2+\alpha\sum_{j=1}^{5}\left|\beta_j\right|\right)\right] \tag{10}$$

3.5. Performance metrics and directional evaluation

The predictions generated are compared with the corresponding actual data. Performance metrics, such as root mean square errors (RMSE) and mean absolute errors (MAE) are computed for every expanding window to assess whether predictive performance improves as the training samples increase. A declining *RMSE* and *MAE* values indicate that the models continue to learn effectively from the additional data subject of the expanding window process. These metrics also serve as the basis to compare benchmark models against the machine learners and identify which model provides the most accurate prediction of bank lending behaviour. Determination coefficients (R^2) are likewise computed to measure the strengths of explained variance to target variables.

$$RMSE=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t)^2} \tag{11}$$

$$MAE=\frac{1}{n}\sum_{t=1}^{n}|y_t-\hat{y}_t| \tag{12}$$

To further the evaluation, the actual data and overall predicted results of target variable were binarised. The objective of binarisation is to determine whether the predictions follow the same direction of the actual data. This became a secondary diagnostic test for prediction outcomes. To do this, the value of a previous quarter is subtracted from the value of the current quarter ($x_t - x_{t-1}$), producing either a positive or negative change. A positive change (or increased tightening) is assigned as 1 and a negative change (or decreased easing) is assigned as –1. Since a neutral outcome does not exist, assignment of any value is not considered.

Then, confusion metrics were computed. The predicted data was compared to the actual data to derive true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). These results were further evaluated using accuracy, precision, recall, F1 score, and false discovery.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{13}$$

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$$F1\ Score = \frac{2\ \times Precision \times Recall}{Precision + Recall} \tag{16}$$

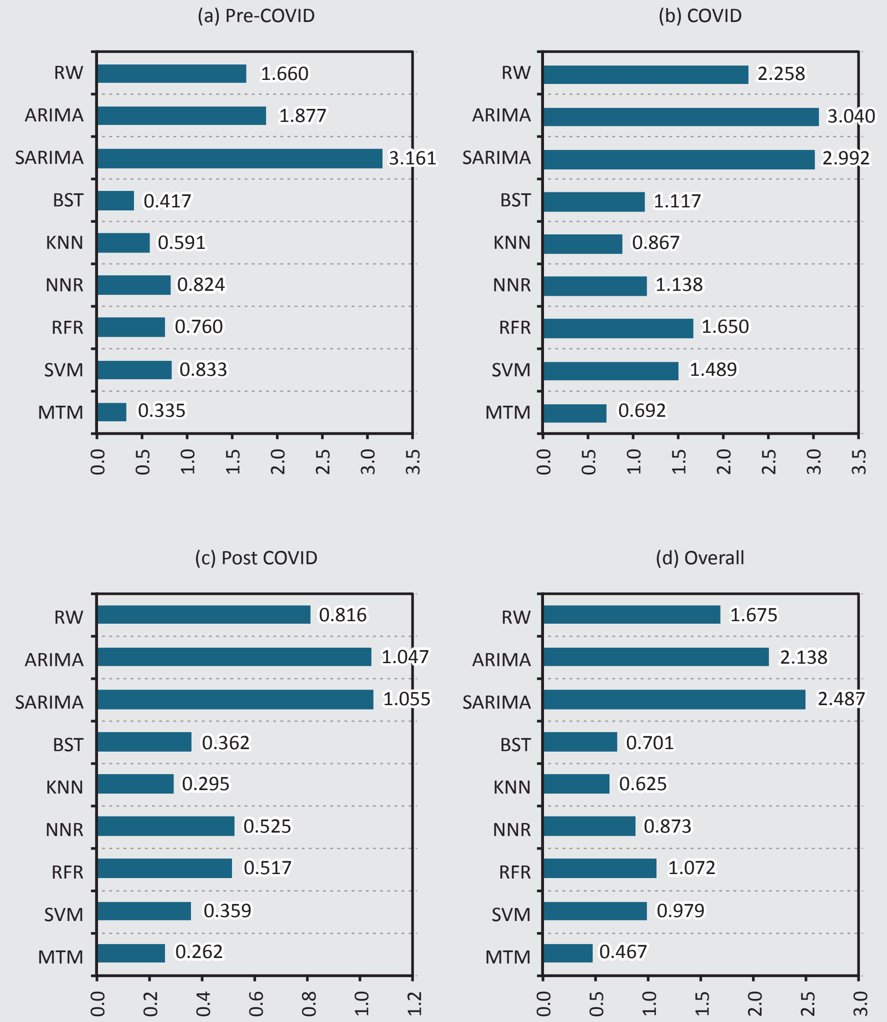
$$False\ Discovery = \frac{FP}{TP + FP} \tag{17}$$

4. Results and discussion

4.1. Prediction accuracy per error metrics RMSE and MAE

Figure 6 compares how well each model predicts lending behaviour across three different periods using average *RMSE*. It measures how far a model's predictions are from actual values. Before the pandemic (2018-Q1–2019-Q4), bank lending behaviour was relatively stable. In this frame, the MTM shows the lowest *RMSE* at 0.335, indicating that it provides the closest predictions to actual SLOS diffusion index. First-layer learners such as BST at 0.417 and KNN at 0.591 also performed reasonably well, but they did not match the consistency of MTM. Meanwhile, benchmark models produce higher errors, showing that they struggle to capture the early patterns in the data.

Figure 6
Average RMSE per window frame of one-quarter-ahead out-of-sample predictions

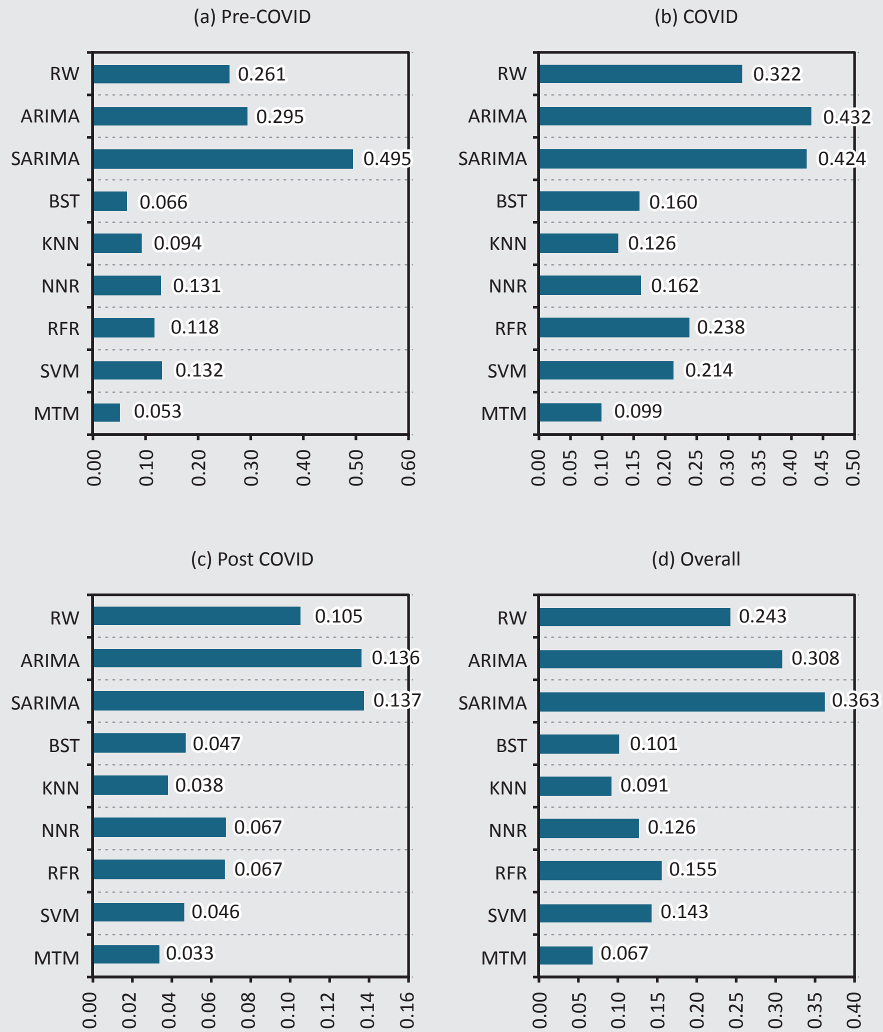


Note: Lower RMSE means better accuracy.

The COVID-19 frame (2020-Q1–2022-Q4) introduced sudden, large swings in lending standards. *Panel (b) of Figure 6* shows that even under turbulent conditions, MTM at 0.692 remains the most accurate among all models ranging from 0.867 to 3.040. All models experienced increase in errors, indicating that they faced difficulty to predict lending behaviour during the pandemic, as they were only trained under normal conditions. As they continued to learn under the expanding-window protocol, their performance in predicting the post COVID frame (2023-Q1–2024-Q4) was more robust, and even better than the pre-COVID frame.

For the whole panel (2018-Q1–2024-Q4), the overall *RMSE* showed that MTM is effective in predicting bank lending behaviour at 0.467. This is followed by KNN at 0.625 and BST at 0.701. The single learners vary in performance depending on the period. Benchmarks remain consistently less accurate across all frames.

Figure 7
Average MAE per window frame of one-quarter-ahead out-of-sample predictions



Note: Lower MAE means better accuracy.

Figure 7 presents the average *MAE* across the three frames. Like *RMSE*, lower *MAE* means better prediction accuracy, and it focuses on the typical size of errors rather than giving extra weight to large mistakes. Across all panels, MTM records the lowest *MAE*, confirming that it consistently produces the smallest average deviation from actual lending standards.

Overall, MTM produces the most consistently accurate quarter-ahead predictions regardless of window frames. Also, first-layer learners outperformed benchmark models, but none surpassed MTM. By complementing both error metrics, MTM not only reduces large errors but also keeps one-quarter-ahead prediction mistakes smaller, making it the most dependable for tracking shifts in bank lending behaviour.

4.2. Overall predictive performance

Table 2 presents the overall performance metrics of benchmark machine learners to determine the most robust and accurate predictive model. Among the individual models, KNN had the lowest *MSE*, *RMSE*, and *MAE*, indicating that its predictions had the smallest average error magnitude and minimal average distance to the actual values. Together with BST and NNR, they were classified as having a strong coefficient of determination, with KNN achieving the highest explained variance. The remaining base learners underperformed relative to the top three, achieving only moderate strength of explained variance and suggesting greater sensitivity to outliers and prediction errors.

Meanwhile, the benchmark models have high errors with weak to moderate explained variance. This shows that using autoregressive terms to account for historical momentum of the SLOS diffusion index is not sufficient to effectively predict lending behaviour. Since baseline learners performed better than benchmark models, bank-specific and macroeconomic indicators are better predictors compared to simple autoregressive patterns.

Table 2
Overall predictive performance of one-quarter-ahead out-of-sample predictions (2018-Q1–2024-Q4)

Model	MSE	RMSE	MAE	R^2	Strength
RW	2.807	1.675	0.243	0.519	Moderate
ARIMA	4.572	2.138	0.308	0.464	Weak
SARIMA	6.185	2.487	0.363	0.340	Weak
BST	0.491	0.701	0.101	0.902	Strong
KNN	0.390	0.625	0.091	0.931	Strong
NNR	0.762	0.873	0.126	0.875	Strong
RFR	1.149	1.072	0.155	0.750	Moderate
SVM	0.958	0.979	0.143	0.846	Moderate
MTM	**0.218**	**0.467**	**0.067**	0.963	Strong

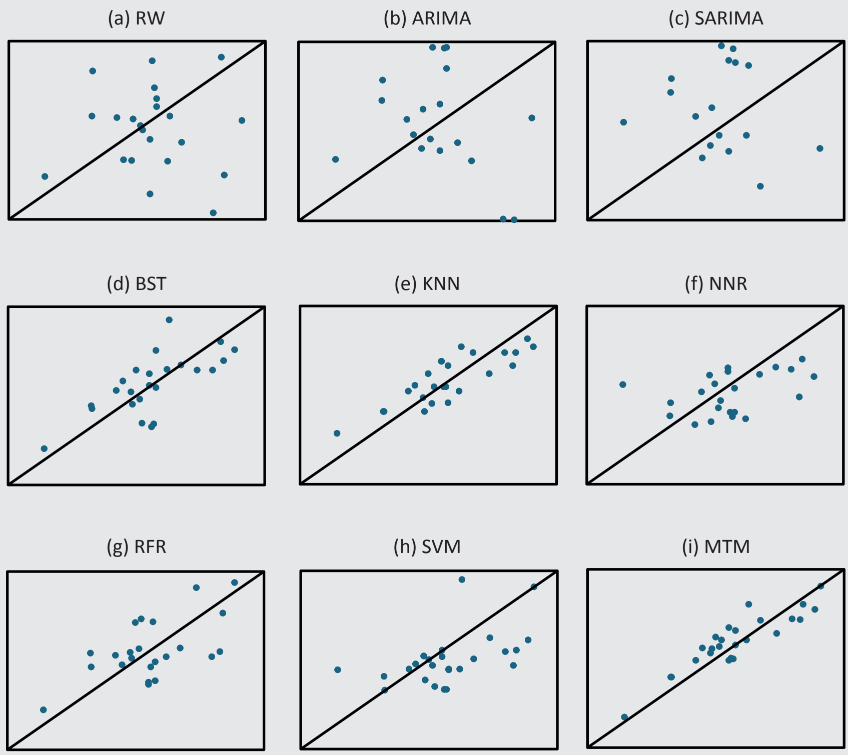
Note: Boldfaced values indicate better performance compared to other models. Values are average for all windows.

Collectively, MTM achieved the lowest errors across all models, confirming its superiority in minimising both overall error magnitude and penalty for large errors while maintaining the strongest predictive power. This establishes MTM as the optimal predictive model for this study. Its core advantage lies in its ability to synthesise the specific strengths of baseline models as they adapt to expanding periods. A key observation from the window-by-window analysis is that the peak performance of individual models is distributed throughout the entire expanded window coverage. This shifting pattern of accuracy is what MTM captures to maintain reliable performance even when baseline models fluctuate.

4.3. Out-of-sample prediction pointwise accuracy

To evaluate the predictive performance of the various predictive tools, *Figure 8* presents panels of scatter plots comparing the pointwise predicted values against the actual observed values on the overall test dataset. The y-axis contains the actual values, while the x-axis contains the predicted values. The diagonal line represents

Figure 8
Pointwise prediction accuracy for one-quarter-ahead out-of-sample predictions



Note: The diagonal line indicates perfect prediction. Proximity to the line reflects model accuracy and calibration.

a perfect prediction where the predicted value equals the actual value. The relative accuracy and calibration of each model can be inferred by the proximity of the data points to this line, with a tighter clustering indicating superior predictive power and lower variance in error.

Benchmark models are scattered far from the prediction line. RW missed major ups and downtrends while ARIMA and SARIMA tended to pull predictions toward average values, resulting in under-predicted high points and over-predicted low points. Meanwhile, first-layer machine learners behaved better. BST captured patterns, but some points overreacted, producing values that jumped too high or too low. KNN produced neat clusters of points as it performed well compared to the rest. NNR had more scattered and inconsistent points with noticeable difficulty finding patterns. RFR generally stayed near the diagonal at middle values, but underpredicted extreme highs, pulling predictions toward safer mid-range levels. Finally, SVM followed a straight trend, but was too rigid to react to sudden changes, leading to scattered points when values moved sharply.

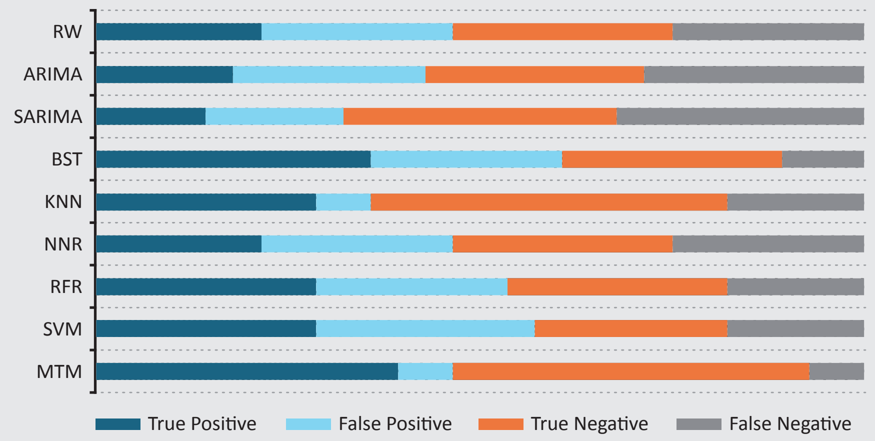
MTM performed most effectively. Most of the points were tightly packed around the diagonal line, showing that its predictions are very close to actual values. It avoids large mistakes, and it captures both gentle and sharp movements in lending behaviour. This pattern reflects the MTM's ability to combine the strengths of all first-layer machine learners while minimising their weaknesses. Hence, MTM is the most reliable predictor of tightening and easing bank lending behaviour.

4.4. Directional accuracy

This study's target variable can be binarised given that a net positive index is equivalent to tightening and a net negative index represents an easing of credit standards. From that, an assessment of how the learners were able to correctly determine directional accuracy was conducted. As shown in *Figure 9*, the predictions are categorised into four components: true positive, true negative, false positive, and false negative. The MTM produced a true positive rate of 0.846, which is higher than the other models that ranged from 0.308 to 0.769. This indicates that 84.6 per cent of predicted positive values were correctly identified as positive based on the actual dataset. Additionally, MTM produced a true negative rate of 0.867, outperforming the rest with results ranging from 0.467 to 0.667. This means that 86.7 per cent of the actual negative values were correctly identified.

In terms of errors, MTM performed more effectively than individual models. The false positive rate is 0.133 similar to KNN, which is notably lower than others that ranged from 0.333 to 0.667. This implies that the probability of a Type 1 error, or incorrectly labelling actual negative data as positive, is only 13.3 per cent. Moreover, the false negative rate of the MTM is 0.154, remaining lower than the rest of the models, which ranged from 0.231 to 0.692. This means that the probability of a Type 2 error, or incorrectly labelling actual positive data as negative, is only 15.4 per cent.

Figure 9
Confusion cardinality metrics of predicted values across models



When evaluating only the individual models, BST performed best at predicting true positive and reducing false negative values. However, it proved to be less effective at predicting true negatives and reducing false positive values. Meanwhile, KNN demonstrated better performance in predicting true negatives and reducing false positives. SARIMA performed the worst in terms of predicting true positives and reducing false negatives.

Table 3
Discriminatory metrics of predicted values across models

Model	Accuracy	Precision	Recall	F1 Score	False Discovery
RW	0.500	0.462	0.462	0.462	0.538
ARIMA	0.464	0.417	0.385	0.400	0.583
SARIMA	0.500	0.444	0.308	0.364	0.556
BST	0.643	0.588	0.769	0.667	0.412
KNN	0.750	0.800	0.615	0.696	0.200
NNR	0.500	0.462	0.462	0.462	0.538
RFR	0.571	0.533	0.615	0.571	0.467
SVM	0.536	0.500	0.615	0.552	0.500
MTM	**0.857**	**0.846**	**0.846**	**0.846**	**0.154**

Note: Boldfaced values indicate superior results compared to other models.

To further determine the directional reliability of the predicted values, the models were further analysed to see whether they can discriminate between tightening and easing behaviour. Results in *Table 3* show that MTM achieved the highest accuracy at 0.857, including precision, recall, and F1 score both at 0.846. This suggests that while baseline models are similarly effective at tracking trends, the MTM can maintain higher performance even during periods of significant volatility, as represented in the actual data. Furthermore, MTM produced the lowest false discovery rate at 0.154 compared to other learners ranging from 0.200 to 0.583.

4.5. Feature importance

Table 4 reports the mean dropout loss for each predictor variable across the five baseline machine learning models. The mean dropout loss based on 50 permutations quantifies the decline in model performance when a feature is removed, thereby serving as a proxy for feature importance. Higher values indicate stronger contributions to predictive accuracy.

Table 4
Permutation feature importance metrics

	Mean dropout loss						
Feature	**BST**	**KNN**	**NNR**	**RFR**	**SVM**	**Average**	**Rank**
Capital Adequacy Ratio	8.514	7.213	10.71	8.679	9.665	8.956	7
Distressed Assets Ratio	8.380	7.169	12.16	7.018	10.331	9.012	6
Earning Assets Yield	10.663	6.802	13.19	6.275	11.141	9.614	4
GDP Growth Rate	8.820	**11.612**	11.80	6.942	10.184	9.872	3
Inflation Rate	8.195	7.438	11.56	6.078	9.512	8.557	9
Past Due Ratio	10.673	8.017	13.61	6.707	**12.132**	10.228	2
Return on Assets	7.958	6.535	12.22	9.141	9.966	9.164	5
Return on Equity	**13.789**	6.633	**14.32**	**9.847**	10.668	11.051	1
Reverse Repurchase Rate	8.109	6.833	12.00	7.242	9.313	8.699	8

Note: Boldfaced values are the highest mean dropout loss per model across the expanded window.

The results reveal several consistent patterns. Return on Equity (ROE) emerges as the most influential feature, ranking first overall with the highest average dropout loss across models. This underscores its central role in explaining lending behaviour, reflecting how profitability strongly conditions banks' willingness to extend credit. Past Due Ratio (PDR) ranks second, highlighting the importance of asset quality and delinquency levels in shaping lending outcomes. Elevated past due exposures reduce banks' risk appetite, making this feature a critical determinant of predictive accuracy.

Other features such as GDP Growth Rate and Earning Assets Yield also rank highly, suggesting that both macroeconomic conditions and the efficiency of asset utilisation materially influence lending behaviour. Their importance confirms the dual role of external economic environment and internal performance metrics in driving credit decisions. By contrast, features such as Inflation Rate and Reverse Repurchase Rate exhibit lower average dropout losses, indicating that while they contribute to the predictive framework, their marginal impact is less pronounced relative to profitability and asset quality indicators.

The finding that ROE and PDR ranked highest, surpassing GDP Growth Rate, suggests that lending behaviour is heavily contingent on a bank's internal capacity to bear risks. Higher profitability enhances this risk-bearing capacity to provide financial flexibility needed to sustain lending activity even during economic uncertainty. Meanwhile, higher PDR reflects the cautionary side of the lending behaviour. Elevated delinquency levels prompt banks to adopt defensive lending policies to safeguard liquidity and satisfy regulatory standards.

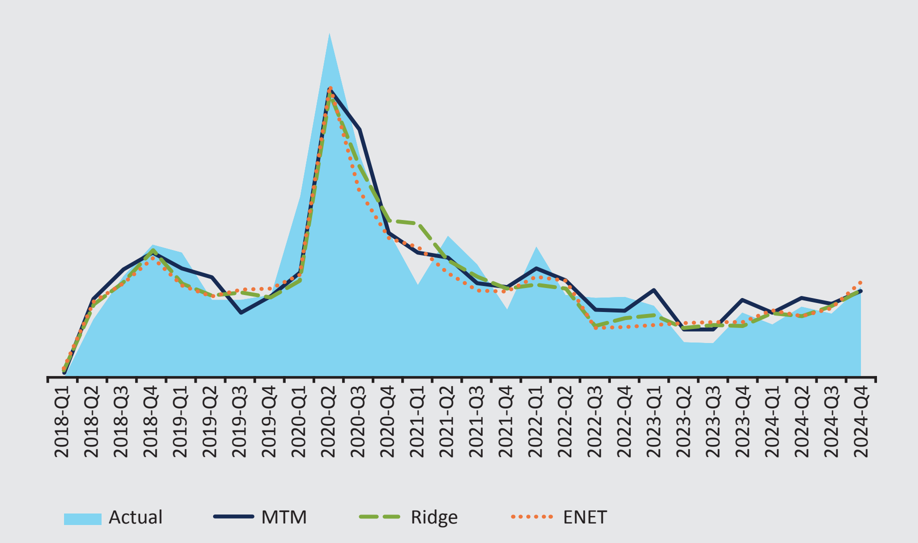
While GDP Growth Rate creates demand for credit, ROE and PDR create a threshold line. Even in periods with high GDP growth, if a bank's profitability is weak or its loan defaults are rising, the supply-side constraints will likely override the demand-side incentives. Hence, banks first ensure their own financial stability before responding to broader economic signals.

The distribution of feature importance across models also highlights methodological diversity. NNR and SVM tend to assign higher dropout losses to profitability and asset quality variables, reflecting their sensitivity to nonproportional interactions. On the other hand, KNN emphasises macroeconomic variables, consistent with its structural bias toward variance explanation. Overall, lending behaviour is most strongly conditioned by profitability measures and asset quality indicators, with macroeconomic growth providing additional explanatory power. MTM benefits from this distribution by synthesising the diverse emphases of individual learners, ensuring that the most informative features are retained while less influential ones are penalised.

4.6. Robustness checks

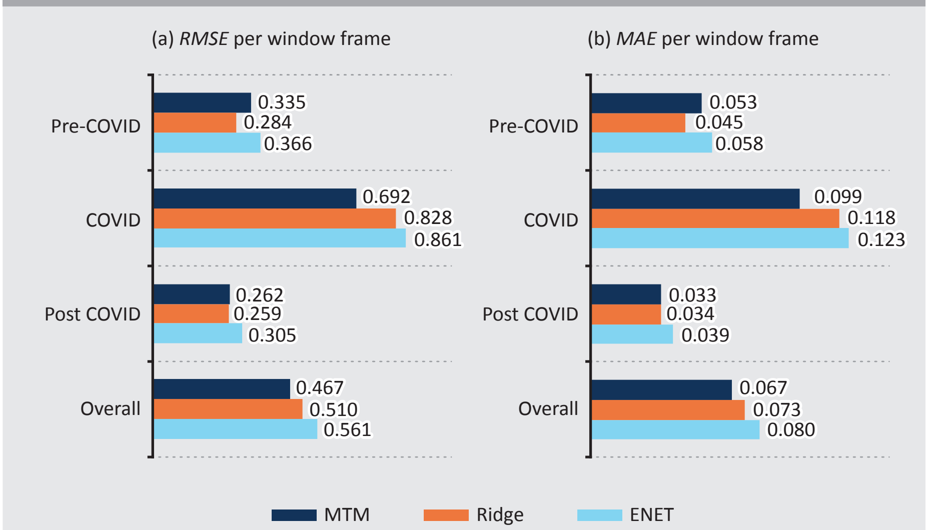
This paper ran two alternative meta-learners to check whether regularising the outcomes of first-layer learners can produce similar results not only with a LASSO penalty. These two alternatives follow the same expanding window process under Ridge and Elastic Net penalties. As shown in *Figure 10*, one-quarter-ahead out-of-sample predictions of the three meta-learners share almost similar capacity to predict bank lending behaviour.

Figure 10
Predictive behaviour of regularised metamodels through LASSO, Ridge, and Elastic Net



The coefficients of determination for the metamodel with Ridge penalty is 0.953 and Elastic Net is 0.960, indicating that the strengths of the metamodel even under the two different regularisation approach is strong. This is further supported by the performance metrics with *RMSE* and *MAE* in *Figure 11* showing minimal differences in their performance.

Figure 11
RMSE and MAE of regularised metamodels through LASSO, Ridge, and Elastic Net



Additionally, feature importance metrics with the same permutations as the first-layer learners show that the mean dropout loss for Ridge and Elastic Net are almost similar to the results of MTM. For Ridge, KNN produced the highest mean dropout loss 8.673 followed by BST at 8.255 and NNR at 7.494. For Elastic Net, BST produced the highest at 8.995, followed by KNN at 6.070 and NNR at 6.468. Those three first-layer learners provided the biggest contribution in predicting bank lending behaviour.

5. Conclusions and implications

This study developed and evaluated a LASSO-regularised meta-learning model that synthesises five machine learners – Boosting, k-Nearest Neighbours, Neural Networks, Random Forest, and Support Vector Machine – to forecast the lending behaviour of Philippine universal and commercial banks. Across an expanding window out-of-sample evaluation from 2009 to 2024, the metamodel delivered lower prediction errors and higher directional accuracy than individual learners and conventional benchmarks. Robustness checks using Ridge and Elastic Net penalties produced similar results and confirmed the stability of the approach.

Moreover, the results highlight several important insights. First, profitability and asset quality emerged as the most influential drivers of lending behaviour. This reinforces the critical role of internal bank performance in shaping credit allocation decisions. Second, macroeconomic conditions such as GDP growth were shown to exert external pressures, reflecting the broader environment in which banks operate. Third, the meta-learning approach demonstrated superior adaptability to extreme events, such as the sudden and significant spike during the COVID-19 pandemic, compared to single machine learners.

These findings carry policy implications for regulators, policymakers, and banking practitioners not just for the Philippines but for other small open economies (SOE) as well.

First, this paper contributes to the global discourse on integrating machine learning in banking supervision. The two-layered metamodeling architecture establishes a forecasting benchmark in data-scarce environments. While advanced economies work on high-frequency big data, many emerging markets face reporting lags and smaller datasets. Hence, the use of meta-learning can extract high-predictive value by balancing the strengths of diverse algorithms.

Second, this paper further justifies the establishment of supervisory technologies (SupTech) for central banks. The reporting lag for bank lending surveys creates a blind spot in monetary policy transmission. Hence, a policy shift toward machine-learning-driven analysis of quarterly financial statements can bridge this gap. The raw financial data already submitted by banks contains sufficient predictive power to forecast their subsequent lending behaviour. Implementing the study's model into a SupTech platform would enhance the proactive measures of central banks in adjusting policy rates and liquidity measures.

Third, monitoring aggregate bank ratios provides early warning indications as deteriorating profitability and asset quality could likely result in the tightening of credit standards. Adopting the model as part of central banks' surveillance toolkit strengthens systemic risk monitoring. Policymakers must anchor policies based on movements of these bank ratios, so that adverse consequences of stress events can be reduced or prevented.

Fourth, the identification of those key drivers offers guidance in designing interventions that strengthen financial stability and resilience. Based on the results, the effectiveness of monetary policy adjustments depends not only on interest rate changes for example, but also to the underlying financial health of banks. Hence, during a crisis such as the COVID-19 pandemic, policy interventions may focus on bolstering bank profitability and cleaning up the balance sheet (supply-side support) as well as on stimulating the broader economy (demand-side support). This ensures that the transmission of monetary policy remains effective given a stable and willing suppliers of credit.

Fifth, the robustness of the model across volatile regimes, including the COVID-19 pandemic, demonstrates its utility in terms of stress testing and scenario analysis. Regulators can use the framework to simulate lending responses under adverse conditions, improving preparedness for future shocks. For instance, stressing the values of bank-specific and macroeconomic indicators based on assumed worst scenarios can predict potential behavioural response of banks. However, it is important to note that while the SLOS diffusion index is a useful proxy for lending behaviour, it reflects perceptions rather than actual loan disbursements. Hence, regulators should treat model outputs as complementary information for decision-making, ensuring balanced reliance on both sentiment and realised lending activity.

Sixth, the Philippine experience provides an example for other SOEs that feature bank-centric financial systems with certain level of exposure to the global economy. In these environments, the meta-learning approach offers a robust method to enhance their early-warning systems, allowing for more precise calibrations of macroprudential tools. For instance, they can use the model to determine the appropriate timing for the release or accumulation of countercyclical capital buffers, consistent with Basel III standards to prevent excessive credit growth during booms and ensuring credit availability during downturns. By identifying a potential easing or tightening of credit standards before it fully manifests, the SOEs can implement pre-emptive measures.

Seventh, insights from the model can inform coordination between monetary and fiscal authorities. For instance, if profitability constrains banks' willingness to extend credit despite accommodative monetary policy, fiscal measures such as credit guarantees or targeted subsidies may be necessary to sustain credit flow to households and businesses.

Finally, for banks, the results underscore the importance of maintaining profitability and asset quality to support strong lending practices. This underscores the importance of having an effective credit risk management system. A loan portfolio that is built on appropriate credit risk management, sound credit granting process, and robust credit measurement and control policies, ensures that credit continues to perform despite stress events. Profitability not only enhances a bank's capacity to absorb shocks, but also provides the flexibility to extend credit under favourable terms, thereby stimulating economic activity. At the same time, strong asset quality reduces credit risk exposure, ensuring that lending growth does not compromise financial stability. Together, these factors highlight that lending is not merely about expanding loan portfolios, but also about balancing growth with resilience. Banks that prioritise profitability and asset quality are better positioned to navigate volatile macroeconomic conditions, align with regulatory expectations, and contribute to the effective transmission of monetary policy.

Future research should expand on this study by extending the framework with other machine learners or considering other bank-specific and macro-economic variables that could further improve the predictive capacity of the metamodel.

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Appendix

A. Publication schedule of features and target

Variable	Report	Data Periodicity	Publication Schedule
SLOS Diffusion Index	Senior Bank Loan Officer's Survey	Quarterly	~ 1 month after the reference period
Capital Adequacy Ratio	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
Distressed Assets Ratio	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
Earning Assets Yield	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
Past Due Ratio	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
Return on Assets	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
Return on Equity	Selected Performance Indicators of Universal/Commercial Bank Group	Monthly	~ 2 weeks after the reference period
GDP Growth Rate	Selected Philippine Economic Indicators	Monthly	~ 2 weeks after the reference period
Inflation Rate	Inflation Rate Press Release	Monthly	~ 1 week after the reference period
Reverse Repurchase Rate	BSP Policy Rates	Daily	1:00 pm every working day

Note: It would take approximately four months to identify the actual bank lending behaviour for a certain quarter. Features are already available approximately two weeks after the previous period (last data of training set). For instance, predicting lending behaviour for December 2024 (to be published in January 2025) would need aggregate bank lending ratios and macroeconomic indicators of September 2024 (data already available on the second week of October 2024). This allows a lead time to implement proactive policies in addressing consequences of either tightening or easing credit standards.

Source: Bangko Sentral ng Pilipinas' Advance Release Calendar https://www.bsp.gov.ph/Statistics/Advance%20Release%20Schedule/AdvanceReleaseSchedule.aspx

B. Stationarity of features and target after first-order differencing

Observation	Augmented Dickey-Fuller t	Phillips-Perron	Remarks
Bank Lending Behaviour	–5.240**	–58.266**	Stationary
Capital Adequacy Ratio	–3.086*	–53.341**	Stationary
Distressed Assets Ratio	–2.459*	–64.660**	Stationary
Earning Assets Yield	–2.133*	–42.927**	Stationary
GDP Growth Rate	–5.658**	–54.070**	Stationary
Inflation Rate	–5.538**	–53.841**	Stationary
Past Due Ratio	–2.217*	–90.611**	Stationary
Return on Assets	–4.541**	–42.638**	Stationary
Return on Equity	–4.909**	–33.919**	Stationary
Reverse Repurchase Rate	–3.354*	–30.629**	Stationary

*Note: *p < 0.05, **p < 0.01.*

C. Normality of residuals of benchmark models and metamodels

Models	Shapiro-Wilk W	p-value	Lilliefors D	p-value	Remarks
RW	0.394	0.962	0.123	0.344	Normally distributed
ARIMA	0.995	0.266	0.106	0.582	Normally distributed
SARIMA	0.939	0.104	0.145	0.140	Normally distributed
MTM-LASSO	0.945	0.171	0.140	0.170	Normally distributed
MTM-Ridge	0.934	0.078	0.138	0.192	Normally distributed
MTM-Elastic net	0.955	0.264	0.143	0.151	Normally distributed

Note: p-values more than 0.05 indicates normal distribution.

D. RMSE window-by-window

Window	RW	ARIMA	SARIMA	BST	KNN	NNR	RFR	SVM	MTM	Ridge	ENET
2018-Q1	0.559	1.118	2.325	0.354	0.822	2.374	0.455	1.717	0.164	0.242	0.280
2018-Q2	0.649	0.170	0.570	0.756	0.548	0.391	0.161	0.143	0.606	0.444	0.546
2018-Q3	1.377	1.916	2.722	0.022	0.344	0.347	0.592	0.947	0.219	0.179	0.214
2018-Q4	3.273	4.643	6.502	0.793	0.577	0.768	0.408	1.591	0.221	0.145	0.379
2019-Q1	4.154	4.333	6.213	0.839	0.336	0.844	1.515	1.390	0.434	0.872	0.937
2019-Q2	2.207	0.887	0.905	0.027	0.733	0.414	1.011	0.002	0.653	0.120	0.105
2019-Q3	0.549	0.518	1.822	0.375	0.724	0.539	0.937	0.182	0.351	0.215	0.289
2019-Q4	0.513	1.432	4.229	0.166	0.641	0.915	1.001	0.693	0.030	0.056	0.177
2020-Q1	1.327	1.484	0.488	1.734	2.803	0.312	3.960	2.410	2.076	2.295	2.148
2020-Q2	5.957	7.164	7.045	4.074	2.691	2.568	6.125	5.596	1.519	1.643	1.431
2020-Q3	3.880	3.895	4.281	0.555	0.605	0.798	1.991	1.783	0.673	0.283	0.967
2020-Q4	1.804	1.697	2.560	0.640	0.707	1.346	0.616	0.002	0.036	0.284	0.169
2021-Q1	0.257	1.984	1.174	1.471	0.700	3.026	2.083	1.601	0.857	1.608	0.982
2021-Q2	1.032	7.161	6.516	0.645	0.368	1.415	0.253	1.357	0.568	0.622	0.954
2021-Q3	5.951	2.494	2.879	0.455	0.581	0.411	0.836	0.566	0.480	0.318	0.661
2021-Q4	3.938	3.203	3.790	0.700	0.576	0.298	1.038	0.001	0.572	0.541	0.456
2022-Q1	0.385	1.020	1.250	0.130	0.790	1.645	1.343	1.739	0.536	0.959	0.741
2022-Q2	0.245	1.853	1.448	0.830	0.415	0.199	0.403	0.648	0.365	0.155	0.366
2022-Q3	1.537	2.688	2.649	1.101	0.067	0.747	0.464	1.075	0.283	0.689	0.723
2022-Q4	0.788	1.837	1.827	1.065	0.107	0.885	0.693	1.097	0.339	0.538	0.734
2023-Q1	0.106	2.065	2.085	0.830	0.106	0.252	0.979	0.800	0.371	0.235	0.470
2023-Q2	2.298	2.093	2.128	0.449	0.361	0.582	0.611	0.001	0.302	0.348	0.474
2023-Q3	1.146	1.557	1.763	0.537	0.365	0.255	0.979	0.365	0.317	0.438	0.491
2023-Q4	0.336	0.600	0.649	0.150	0.362	0.625	0.126	0.455	0.296	0.332	0.231
2024-Q1	0.653	0.632	0.707	0.473	0.442	0.400	0.477	0.101	0.286	0.256	0.324
2024-Q2	0.038	0.264	0.182	0.162	0.279	0.395	0.245	0.211	0.218	0.219	0.224
2024-Q3	0.668	0.352	0.289	0.171	0.013	0.578	0.279	0.175	0.217	0.166	0.123
2024-Q4	1.288	0.813	0.637	0.125	0.431	1.117	0.442	0.765	0.089	0.080	0.102

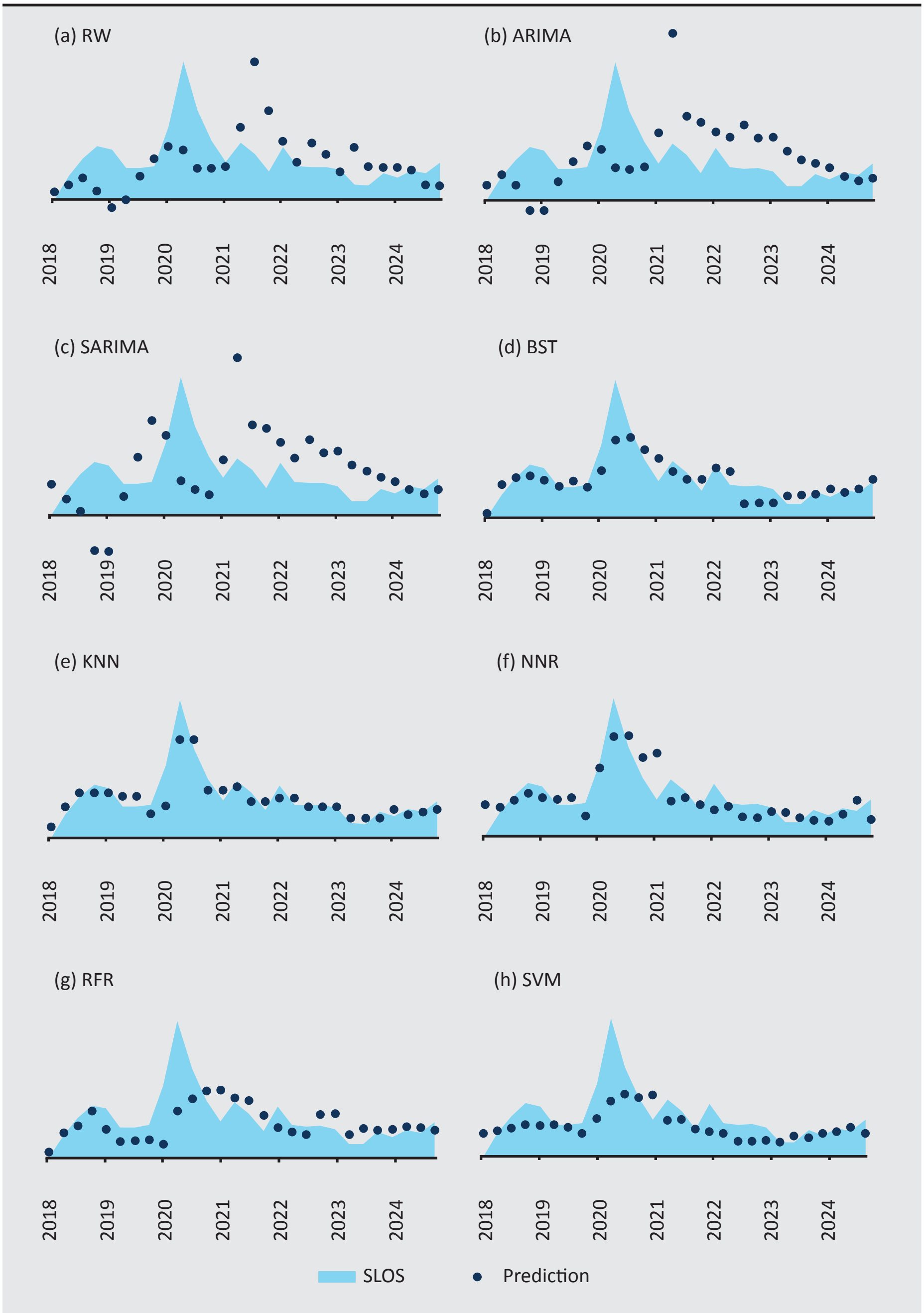
E. MAE window-by-window

Window	RW	ARIMA	SARIMA	BST	KNN	NNR	RFR	SVM	MTM	Ridge	ENET
2018-Q1	0.092	0.184	0.382	0.058	0.135	0.391	0.075	0.282	0.027	0.040	0.046
2018-Q2	0.105	0.028	0.093	0.123	0.095	0.064	0.026	0.023	0.098	0.072	0.089
2018-Q3	0.221	0.307	0.436	0.004	0.055	0.056	0.095	0.152	0.035	0.029	0.034
2018-Q4	0.518	0.734	1.028	0.125	0.091	0.121	0.065	0.252	0.035	0.023	0.060
2019-Q1	0.649	0.677	0.970	0.131	0.052	0.132	0.237	0.217	0.068	0.136	0.146
2019-Q2	0.341	0.137	0.140	0.004	0.113	0.064	0.156	0.000	0.101	0.018	0.016
2019-Q3	0.084	0.079	0.278	0.057	0.111	0.082	0.143	0.028	0.054	0.033	0.044
2019-Q4	0.077	0.216	0.638	0.025	0.097	0.138	0.151	0.105	0.005	0.009	0.027
2020-Q1	0.198	0.221	0.073	0.259	0.418	0.047	0.590	0.359	0.310	0.342	0.320
2020-Q2	0.878	1.056	1.039	0.601	0.397	0.379	0.903	0.825	0.224	0.242	0.211
2020-Q3	0.566	0.568	0.625	0.081	0.088	0.117	0.290	0.260	0.098	0.041	0.140
2020-Q4	0.260	0.245	0.370	0.092	0.102	0.194	0.089	0.000	0.005	0.041	0.024
2021-Q1	0.037	0.283	0.168	0.210	0.100	0.432	0.298	0.229	0.122	0.230	0.140
2021-Q2	0.146	1.013	0.922	0.091	0.052	0.200	0.036	0.192	0.080	0.088	0.135
2021-Q3	0.833	0.349	0.403	0.064	0.081	0.058	0.117	0.079	0.067	0.045	0.093
2021-Q4	0.546	0.444	0.526	0.097	0.080	0.041	0.144	0.000	0.079	0.075	0.063
2022-Q1	0.053	0.140	0.172	0.018	0.109	0.226	0.185	0.239	0.074	0.132	0.102
2022-Q2	0.033	0.252	0.197	0.113	0.057	0.027	0.055	0.088	0.050	0.021	0.050
2022-Q3	0.207	0.362	0.357	0.149	0.009	0.101	0.063	0.145	0.038	0.093	0.098
2022-Q4	0.105	0.246	0.244	0.142	0.014	0.118	0.093	0.147	0.045	0.072	0.098
2023-Q1	0.014	0.274	0.276	0.110	0.014	0.033	0.130	0.106	0.049	0.031	0.062
2023-Q2	0.302	0.275	0.279	0.059	0.047	0.076	0.080	0.000	0.040	0.046	0.062
2023-Q3	0.149	0.203	0.230	0.070	0.048	0.033	0.128	0.048	0.041	0.057	0.064
2023-Q4	0.043	0.077	0.084	0.019	0.047	0.081	0.016	0.059	0.038	0.043	0.030
2024-Q1	0.084	0.081	0.091	0.061	0.057	0.051	0.061	0.013	0.037	0.033	0.042
2024-Q2	0.005	0.034	0.023	0.021	0.036	0.050	0.029	0.027	0.028	0.028	0.025
2024-Q3	0.084	0.044	0.036	0.022	0.002	0.073	0.035	0.022	0.024	0.021	0.015
2024-Q4	0.161	0.102	0.080	0.016	0.054	0.140	0.055	0.096	0.011	0.010	0.013

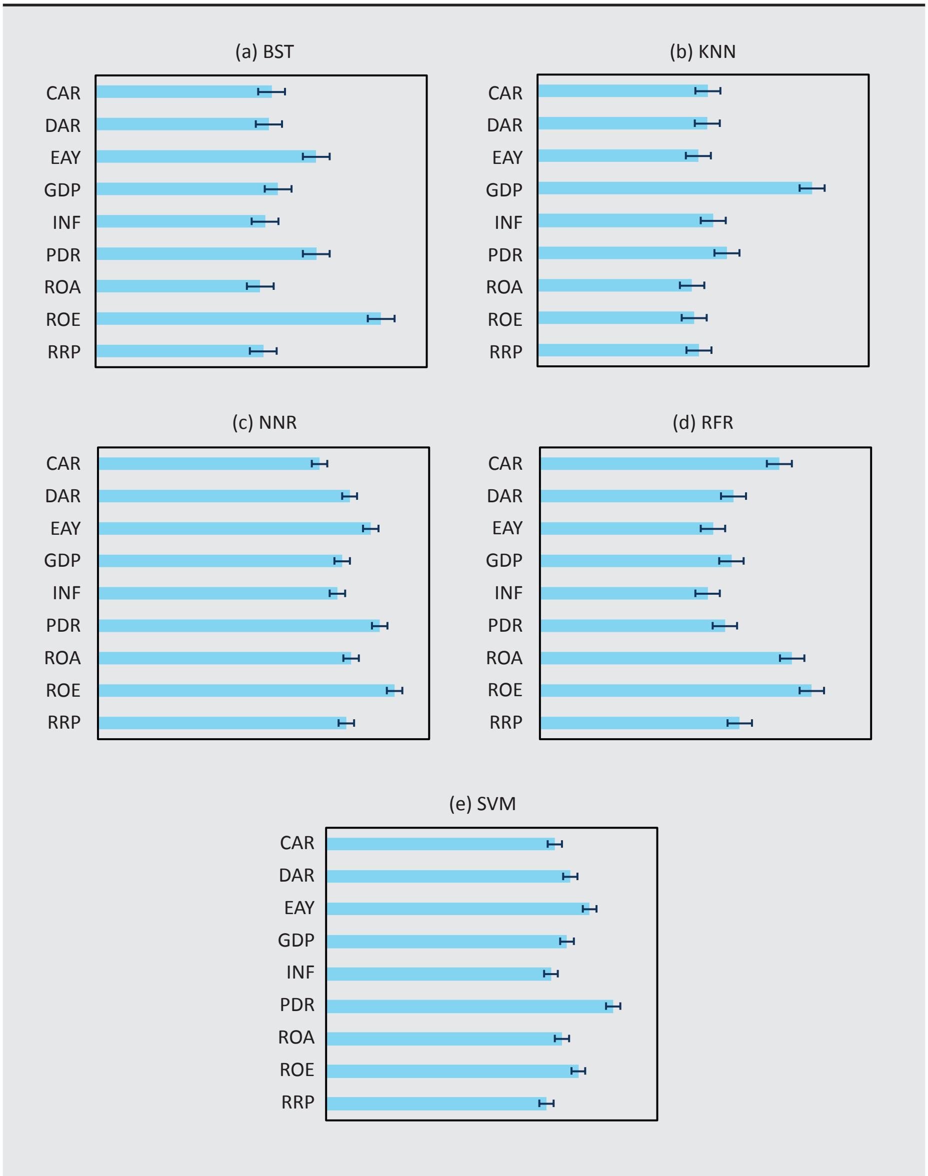
F. Binarised prediction results of benchmark and first-layer models

	TP	FP	TN	FN	TP Rate	FP Rate	TN Rate	FN Rate
RW	11	2	13	2	0.846	0.133	0.867	0.154
ARIMA	8	8	7	5	0.615	0.533	0.467	0.385
SARIMA	8	7	8	5	0.615	0.467	0.533	0.385
BST	6	7	8	7	0.462	0.467	0.533	0.538
KNN	8	2	13	5	0.615	0.133	0.867	0.385
NNR	10	7	8	3	0.769	0.467	0.533	0.231
RFR	4	5	10	9	0.308	0.333	0.667	0.692
SVM	5	7	8	8	0.385	0.467	0.533	0.615

G. Predictive behaviour of benchmark and first-layer models



H. Mean dropout loss of features based on 50 permutations with whiskered standard errors



I. Feature importance of alternative metamodels

	MTM	Ridge	ENET
BST	7.355	8.255	**8.955**
KNN	**13.796**	**8.673**	6.070
NNR	8.716	7.494	6.468
RFR	7.115	7.324	5.124
SVM	7.115	7.266	5.124

Note: Mean dropout loss based on 50 permutations.

J. Regression coefficients based on the last expanded window