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RESEARCH ARTICLE

Forecasting and Evaluation of Non-Performing Loans in the Turkish Banking Sector

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Abstract
In recent years, there is an increasing trend in non-performing loan levels in Turkey which causes stress both on the real and financial sectors. Increasing non-performing loan volumes are an indication of problems in sectors or the general economy. It is also closely related with the stability of the banking system. It is therefore important for regulatory/supervisory institutions and banks to be able to predict problematic loan levels successfully, for better policy making and management. For this purpose, non-performing loans to credit ratio in Turkey for the dates between the first quarter of 2015 and fourth quarter of 2019 were forecasted with two machine learning methods, namely random forests and boosted trees, by using data starting from the first quarter of 2003. Lagged values of several macroeconomic, bank-specific and uncertainty factors are included as determinant variables in the analyses. Methods provide insight about the relationship of included variables with non-performing loans. Our results indicate partial dependencies and positive relationship between non-performing loans and inflation, interest rate and capital adequacy ratios, and negative relationship with credit to gross domestic product ratio.

Keywords

Banking Regulations, Financial System, Time-Series Forecasting, Machine Learning

Introduction

A well-functioning financial market transfers funds from people who have an excess funds and do not have a productive use for them to those who have a shortage of funds. In the modern era, efficiency of this transfer process fuels real economic activity, therefore, soundness of the financial system has vital importance for sustainable economic growth. The structure of financial markets and efficiency of financial intermediation have direct impact on the economic conditions of different countries (Mishkin, 2007).

A significant development has been achieved in the financial system of Turkey with the implementation of a reform package after 2001, in response to the infamous banking crisis in that year. Indeed, there are still some structural problems in the financial system, like

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inadequate inclusion of non-bank financial institutions to the system and insufficient volume of capital markets. The largest share in the financial sector belongs to banks (around 85%) (Banking Regulation and Supervision Agency of Turkey, 2019). For this reason, the health of Turkish banking system and banks' strong balance sheets are important for the whole economic system.

There are various factors, which would affect financial the health and the balance sheet structure of the banking system. Credit risk, which is one of the most important among those factors, must be managed by banks along with other risk factors like market risk, foreign currency risk and operational risk.

Non-performing loans (NPLs) are one of the most important indicators of the financial health of banks and constitute the main measure of credit risk in the banking system (Kjosevski, Petkovski, & Naumovska, 2019). A balance sheet item can be defined as a loan that is several (three in Turkey) months overdue or in default, and has direct effect on bank performance, liquidity, and profitability. .

NPL volume of a bank is an especially important component within its credit management processes (Poudel, 2012) and are closely monitored by bank management and regulators due to implications on bank performance and overall economy. Insolvency of banks is closely related with asset quality deterioration. One of the reasons of asset quality deterioration of banks are NPLs.

Financial stability of the banking system in a country has always been affected by the NPL volume. It has a direct negative effect on banks' balance sheets by decreasing the loanable funds, decreasing profitability, and creating indirect burden for all parties in the economy, specifically for borrowers, lenders, and intermediaries. It also has a strong relationship with banking crises. Reducing problematic loan volume has a positive impact on the medium-term economic performance of a country (Balgova, Nies, & Plekhanov, 2016; Ozili, 2019). It is normal to observe fluctuations in NPL volumes in a country, especially due to business cycles or shocks that disturb regular economic activity. But real danger arises if there is a positive trend in the volumes, parallel to low/negative growth, high unemployment and credit booms.

This study attempts to build a reliable forecasting model, by using several macroeconomic, bank-specific and uncertainty indicators. The main objective is to understand if it is possible to forecast future non-performing loan to credit ratios (NPL ratio) by using these indicators as leading variables, and if so, to what extent. Successfully forecasted NPL ratios may provide valuable information and chance to policy makers to respond situations more proactively. As a secondary objective, by using information provided by implemented models, important variables on forecasts are determined. It is important to note that it will not be possible to interpret these information as "causal inferences"; but more like "signal inferences". The analysis period starts from the beginning of 2003 and ends at the end of 2019, just before global pandemic crisis started. So, the effect of the pandemic on NPL ratios is not investigated in this analysis.

From this point on, the study continues with an examination on how the NPLs evolved after the stabilization program (namely "Transition to the Strong Economy Program") initiated in the Turkish Banking system. Then, literature is given on the choice of determinant variables of NPL ratios along with several prediction attempts on NPLs in Turkey and other countries. Next, a brief rationale for our model preference is given, and after, the methodology section provides more information on the data, implemented methods and how the performance of methods is evaluated. Results are presented, interpreted and discussed along with policy recommendations and comparisons with the literature.

Evaluation of Non-performing Loans in the Turkish Banking System

Turkey experienced two banking sector crises in November 2000 and February 2001. However, even before the crisis period, the previous years were also very unstable for the Turkish economy. Nearly the whole 90s passed with high inflation and uneven growth rates. In Figure 1, NPL ratios are given for the period between 1988 and 2019, as annual data.

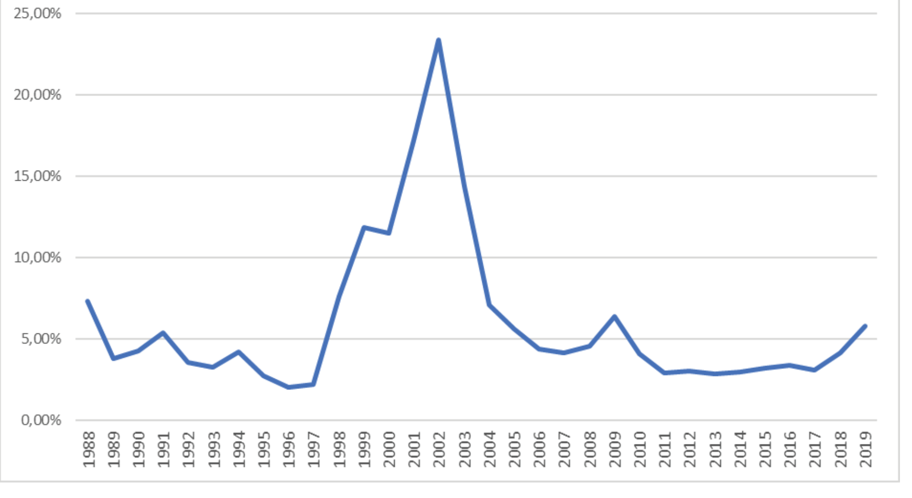

Figure 1. NPL to credit ratio in Turkey (1988-2019)

Own elaboration by using data from CBRT

The main weakness of Turkish economy in 90s was high public debt levels. In those years, the financial system in Turkey was in a developing stage. In 1989, restrictions on capital movements and foreign borrowing by residents were removed. This liberalization enabled more capital inflows to Turkey. But capital inflows were mostly speculative, and investors did not use the liquidity in the market in a productive manner; combined with increased public expenditures financed by these available funds (Yentürk, 1999), Turkey experienced high inflation rates without a significant change in unemployment and an advance in economic growth. Eventually, Turkey found itself in a currency crisis.

According to regulations in Turkey, NPLs are defined as the sum of impaired loans (loans with specific provisions) and the non-impaired loans that are overdue for more than 90 days. Overall, NPL ratios until 1998 were lower than 5%. But after 1998, especially with a surge in credit growth in 1999, problematic loan levels reached remarkably high levels. After the crisis in 2000 hit Turkey, overnight interest rates skyrocketed (to 4,000% levels) and the Turkish Lira depreciated by more than 50% in three months. By the end of 2001, the annual NPL ratio was 17.2% and by the end of 2002, it was 23.26%. Many banks went bankrupt during the crisis (Gormez, 2008).

At the onset of the 2000-2001 crisis, the Turkish economy was highly dependent on short-term capital inflows. Interest rates were also very volatile. As Orhangazi (2014) pointed, increased capital inflows correlate with credit expansion and are closely related with economic growth in Turkey. Slowdown in capital inflows, and even a negative net outflow in 2001, pushed the economy into recession.

In those years, the banking system was fragile due to systematic risks they were exposed to. Risks in the banking system can be summarized as maturity mismatches (funding long term government securities with short term deposits), ineffective supervision, and continuing open foreign currency positions. The share of the state-owned banks in the financial sector was around 30%, and they suffered big losses for subsidizing some sectors parallel to the economic policies of the government. During 1999 to 2001, 18 banks, which is equivalent to 12% of the total assets in the banking sector, were taken under the control of the Saving Deposit Insurance Fund.

After the crisis, a detailed economic program and structural reforms were implemented to overcome overwhelming structural problems (Ozatay & Sak, 2002). Loans to the manufacturing sector were especially problematic. To restructure the debt of manufacturing companies, which were unable to repay their debts, a new program was implemented that was named the İstanbul Approach with Law No.4743 Restructuring Debts to Financial Sector (Finansal Yeniden Yapılandırma Koordinasyon Sekreteryası, 2005). These kinds of legal frameworks and governance are crucial for tackling the NPL problem. There are several examples of financial restructuring programs that were launched in many countries for making an agreement between debtors and banks providing out-of-court mediation. The centralized out-of-court debt workout program was used by the governments of Korea, Thailand, Indonesia and Malaysia in the 1990s (Woo, 2000).

The NPL ratio in Turkey is generally lower than in Europe and the World. On the other hand, an upward trend is seen with the impact of the Global Financial Crisis in 2008 (to 6.4% in 2009, from 4.16% in 2007; see Figure 1). Increases in the NPL ratio have become evident in recent years, which are generally concentrated in private corporations. Currency shocks is an important factor behind this surge, as years of relatively cheap foreign exchange rates promoted credits on foreign currency.

Foreign currency lending is common for developing and transition countries and borrowers of foreign currency loans expect low interest rate advantages. Depending on the exchange rate fluctuations, the expected advantages may turn easily into disadvantages for the borrowers and banks. The ratio of foreign currency loans to total loans ratio in Turkey was 28% at the end of 2013, and it has increased to 40% by the end of 2018, and it was 38% of the total loans at end of 2019 (Banking Regulation and Supervision Agency of Turkey, 2019). Because of this high share of foreign currency denominated loans in Turkey, sharp depreciations in Turkish Lira caused an increase in the NPL level.

Banks and investors held meetings in 2018, regarding selling or transferring of the bad loans into special funds, but talks were not finalized and stalled over. The Banking Regulation and Supervision Agency (BRSA) announced that a total of TL 46 billion worth of loans (more than 8 billion USD) should be written off by banks (Banking Regulation and Supervision Agency of Turkey, 2019). Like the İstanbul Approach, a new Financial Restructuring program was introduced by BRSA on 15.08.2018 (named Regulation on Restructuring the Financial Sector Debts). But while these efforts have been established to reduce problems on one side, more credits are pumped to small and medium size firms through the Treasury-backed Credit Guarantee Fund on the other side. More recently, credit acceleration policies were applied via state banks and with legal enforcements (like asset ratio).

How Non-Performing Loans Affect The Bank Balance Sheet

Loans are one of the most important components of bank balance sheets and obviously one of the key sources of their profits. As in many countries, banking loans are the main source of corporate finance and economic growth in Turkey. Apparently, the quality of bank loan portfolios and NPL levels are essential for banks. Banks with high NPL ratios could face liquidity, profitability and capital adequacy problems. The increase in NPL in the majority of the banking sector has seriously threatened financial stability, as in the 2007- 2008 global mortgage crises.

NPLs can cause cash inflow to decrease because of the loan principal and interests not collected on maturities, and liquidity problems may increase. Munteanu (2012) concluded that the NPL ratio has a constant significant negative influence on bank liquidity determinants in Romania over the 2002-2010 period. (Munteanu, 2012). On the other side, banks cannot concentrate on their main activities while trying to eliminate this problem. This leads to a decrease in the efficiency of banks' credit management and loan allocation process. Due to legal regulations, banks are obliged to allocate provisions for their NPLs that are deducted from the net interest income, and therefore, the profits of the banks are negatively affected.

The sum of bad loans and bank failures are interrelated. The NPL volume in the financial sector increases the possibility to put the bank in financial difficulty and profitability problems. The deterioration of balance sheets will result in bankruptcies and real sector financing declines because of the lack of available capital/funds. There is a consensus on the view that high NPL levels have a negative impact on the lending capacity of banking sector; e.g. bank lending to non-financial firms has decreased when the NPL ratio has increased (European Central Bank Banking Supervision, 2017). When countries manage to reduce their NPL ratios in the system, they experience faster growth rates. There is an inverse relationship between economic growth and the NPL ratio, positive growth rate of gross domestic product (GDP) decreases NPLs (Dimitrios, Helen, & Mike, 2016; Louzis, Vouldis, & Metaxas, 2012; Makri, Tsagkanos, & Bellas, 2014; Messai & Jouini, 2013; Us, 2018).

The NPL level of banks affects their lending capacity through three different channels, specifically profitability, capital adequacy and funding capacity. When the NPL volume increases, banks must increase provisions, which lowers the income of banks. Provisions may also tie up a significant sum of capital due to higher risk weights on harmed assets. A weakened balance sheet makes bank's funding costs higher. The combined effect of these channels increases lending rates, decreases lending volumes and increases the risk of the bank (Aiyar et al., 2015; European Central Bank Banking Supervision, 2017). The impact of credit risk management on the financial performance of commercial banks has been analyzed in Nepal (Poudel, 2012), and it indicated that banks need to allocate more efforts to default rate management.

The capital adequacy of banks is one of the main pillars for absorbing potential losses. Kozaric and Zunic (2015) analyzed the relation between NPL and capital adequacy in the Bosnia and Herzegovina banking system and found a strong negative correlation between them (Kozarić & Žunić, 2015). In order to limit negative consequences, regulatory authorities closely watch the allocating loan provisions and loss coverage policies.

Literature Review on Non-Performing Loans and Its Determinants

In order to obtain successful forecasts on NPL ratios, the determination of variables to include into the models matters a lot. The inclusion of irrelevant variables do not possess a problem for the methods employed in this study but excluding relevant variables, thus ignoring important information may reduce performance. In this section, a review on the choice of variables in the studies is given.

The literature on NPL focuses on different aspects of the topic. Some of the studies focus on financial vulnerability and crises related with the volume of NPLs in economies, with an increased attention after the global financial crisis. These studies have emphasized that NPLs can be used as an indicator of banking crises and have analyzed how a macro prudential policy can play an important role preventing system-wide increases in NPLs (Reinhart & Rogoff, 2011; The European Systemic Risk Board, 2019). Another group of studies examine the relationship between financial development and NPLs, and the economic consequences of reducing nonperforming loans (Balgova et al., 2016; Ozili, 2019).

Identifying the factors affecting the NPL levels in an economy provides valuable information to support efforts to prevent adverse outcomes (Makri et al., 2014; Messai & Jouini, 2013). There are some other studies forecasting NPLs using macro and micro variables (Greenidge & Grosvenor, 2010). Another study was conducted with the forecasting models regarding recovery rates of NPLs using a private database from a European debt collection agency (Bellotti, Brigo, Gambetti, & Vrins, 2021).

Variables considered regarding the NPLs prediction in the literature can be categorized in two main groups. The first one is the macroeconomic variables, and the second one is bank-specific variables. GDP growth, unemployment rate, inflation rate, government budget balance, public debt as percentage of GDP, interest rates are frequently used macroeconomic variables in analyses. From the bank-specific variables, capital adequacy requirement of the banks, efficiency of banks, the loan deposit ratio is found to be included.

As mentioned before, the NPL ratio and the GDP growth have an inverse relationship and most of the studies indicate that banks' problematic loans are closely related to economic and business cycles. When the growth rate of an economy declines, earnings of firms and households decay and it becomes difficult for them to fulfill their liabilities. When the economy has higher growth rates, the debt servicing capacity of firms and households increase (Dimitrios et al., 2016; Makri et al., 2014; Messai & Jouini, 2013; Salas & Saurina, 2002; Us, 2018). However, in Vatansever and Hepsen (2013)'s study, the GDP growth was not found significant for explaining the NPL ratio in Turkey.

Studies inquiring the factors affecting the NPL ratios indicate a strong positive correlation with unemployment rates. It is widely accepted that reducing unemployment and increasing income improve the financial condition and payment ability of borrower's loan installments (Dimitrios et al., 2016; Louzis et al., 2012; Makri et al., 2014; Messai & Jouini, 2013).

There are significant number of studies which included inflation rate into their analysis on NPL ratios. The inflation rate's impact on NPLs is not clear and the relationship can be either negative or positive (Arrawatia, Dawar, Maitra, & Dash, 2019; Khan, Ahmad, Khan, & Ilyas, 2018; Nkusu, 2011); and some studies even indicate that inflation does not have any significant impact (Makri et al., 2014).

Government budget balance, public debt as a percentage of GDP and interest rates are other indicators included in studies. Public debt is an important indicator of the fiscal structure of a country and a low debt promotes financial stability and a healthier banking system. Higher debt levels are expected to be accompanied with higher NPLs. This relationship also implies that fiscal problems might lead to an increase in problematic loans (Louzis et al., 2012; Makri et al., 2014; Us, 2018). In contrast, Dimitrios et al. (2016) reported that there is no significant relation between fiscal policy, debt and NPLs.

Among bank-specific factors, the capital adequacy ratio is one of the most frequently used but the results are conflicting. Some of the studies indicate a positive relationship between the capital adequacy level and the NPL level in banks. Vatansever and Hepsen (2013) indicated a positive relation between these variables. In their model, when return on equity (ROE) increased by 1 point, then, the NPL rate increased by 0.15. On the other hand, some of the models indicate a negative relation between these variables. When the capital requirements are enforced by law and capital adequacy ratios improve, there will be an improvement on loan quality and NPLs will be lower (Makri et al., 2014).

In a study using the data of 59 countries, empirical results show that an increased capital adequacy ratio and better provisioning policies seem to reduce the level of problem loans (Boudriga, Taktak, & Jellouli, 2009). Berger and DeYoung (1997) report a negative link between the capital requirement and NPLs, which asserts that less capitalized banks are more likely to take risks and a low capital ratio is associated with higher NPLs.

Another important bank-specific factor is the efficiency of banks, which can be measured in different ways. In Berger and DeYoung's (1997) study, Granger-causality tests were conducted, and they concluded that bad management and moral hazard hypotheses explained a significant part of NPLs. Sstudies which used the ratio of other expenses to assets as an indicator for managerial efficiency found a positive relationship with NPLs (Louzis et al., 2012; Us, 2018). In another paper, empirical evidence was provided by investigated causality between the cost efficiency and NPLs for the Czech Republic's banking industry. They extended the Granger-causality framework used by Berger and DeYoung (1997), and provided support for bad management hypothesis, and stated that inefficiency in bank management resulted in an increase in NPLs (Podpiera & Weill, 2008).

Several studies found that a significant and negative relationship between the return on assets and the amount of NPLs. It is clear that banks that are not under pressure to increase their profits do not extend risky loans (Dimitrios et al., 2016; Messai & Jouini, 2013). Return on assets and loans to deposit ratios are indicators of quality and riskiness of management. Loans to deposit ratio is another bank-specific variable that is taken into account for explaining NPLs and expectedly, the ratio has a positive correlation with the NPL ratio (Dimitrios et al., 2016; Makri et al., 2014). This ratio is a proxy of the total debt burden of households and companies, and it reflects banks' risk-taking attitude. High debt burden is negatively correlated with NPLs in economic upturn periods, in economic downturn periods, it would be positively correlated (Nkusu, 2011).

Some other studies found a positive relation between credit to deposit ratio and NPLs. This relation states that an increasing credit to deposits ratio reveals a risk preference and is expected to lead to higher NPLs (Dimitrios et al., 2016). Lastly, it is found that the NPL of previous year is one of the major contributors to the deterioration of the current year NPL (Arrawatia et al., 2019).

Methodology

In this study, the NPL ratios in deposit banks functioning in Turkey are forecasted by two machine learning (ML) methods, namely Random Forests (RF) and Boosted Trees (BT). Predictor variables included in forecasting models are selected parallel to the literature. Additionally, several uncertainty measures are added to the models.

Data

The dataset comprised of sixteen variables, including the NPL ratio. Predictor variables consist of three banking-sector specific factors, eight macroeconomic factors, three global and country specific uncertainty measures and one dummy variable to distinguish recession eras for Turkey. In the preliminary examination, twenty-one variables were included in the dataset; but it is seen that some of these variables are closely related to each other (with very high correlation scores up to 0.97; preliminary examination results are presented in supplementary material). For this reason, some of these variables are dropped from the dataset, or combined to capture average information. Details and sources of data can be found in supplementary materials.

In conventional and commonly used econometric methods, it is a necessity to work with non-stationary data, because most statistical methods require an assumption of stationarity on time-series, and a violation of this assumption may lead to spurious results. Most time-series exhibit non-stationary behaviors, meaning that the statistical properties like mean and variance may change over time, and thus, will prevent inferential analyses. Transforming data by differencing is usually used to make time-series stationary, but as López De Prado (2018) points, this action will erase some important information about past (memory) that costs less predictive power[1].

1 There are different views on the effect of non-stationary time-series on predictive power of models. Even López De Prado (2018) says stationarity is a necessity for supervised learning (e.g. RF and BF), there are many studies that employed non-parametric methods and successfully used non-stationary time-series for prediction purposes (see Changqing et al. (2015)).

Consequently, in order to reveal time-varying statistical properties of data, stationarity tests (i.e. augmented-dickey fuller- ADF) are conducted on the time-series used in this study. It is seen that there is a mixture of integrity order, I(0) and I(1), among variables (see supplementary materials). But to preserve and use the long-term memory of time-series, no transformation is made on the data, they are used as in their raw forms.

The analysis period covers the dates between 2003:Q1 and 2019:Q4; or in other words, includes the reform years after 2001 and end just before the pandemic crisis. Quarterly observations are adopted because most of the macroeconomic data are not available in higher frequencies. The whole dataset has 68 observations, but with inclusion of lags into the models, the total observation number will vary from 67 (for 1 lag) to 64 (for 4 lags).

Predictive Models

In this study, two powerful ensemble trees, random forests (RF) and boosted trees (BT) are implemented to forecast NPL in Turkey, by using several macroeconomic and banking sector indicators. These methods are preferred because many determinant variables (and their lags) are included, there is a high probability that relationships and interactions among variables may be too complex to be modelled properly with conventional econometric approaches. Relatedly, statistical properties and structures of time-series may not be suitable for direct implementation, and many structural breaks due to business cycles may exist over the analysis period. RF and BT provide opportunity to bypass such observable and unobservable issues.

The simplest example of tree based methods is the classification and regression tree (CART). In CART with regression setting, a single tree is created by partitioning the data into smaller groups that are more homogenous with respect to the response (Kuhn & Johnson, 2013). Homogeneity is ensured by selecting a predictor with a split value that minimizes errors over the groups[2]. This splitting procedure continues until a termination condition is met. We used CART to build a benchmark model and compare the performance of RF and BT.

Random Forest

CARTs are highly successful for learning on training data and provide highly interpretable outcomes for analysts, but they are also subject to a high variance[3] problem. RF (Breiman, 2001) provide an improvement over CARTs (and several options used to lower variance like pruning and bagging) by constructing a “forest” consisting of decorrelated trees. In RF, many

2 A group’s prediction for the response is the mean of observations’ response values within the group. Errors are then calculated as the difference between actual response values and the mean.

3 A method with high variance will give quite different outcomes for every distinct training data, thus lacks generalization ability.

trees are created on bootstrapped samples, and each split decision is made by considering only a subset of all the original predictors. This last property provides a chance to capture every possible information from all predictors, otherwise impossible if strongly informative predictors exist; because initial splits will mostly be dominated by those few predictors, and this may result in similar trees. By removing restrains on other predictors, many distinct trees may exist, and a substantial reduction in variance will be achieved. In many studies, RF are found highly efficient especially for prediction purposes.

Boosted Trees

Trees with the Friedman's gradient boosting machine (Friedman, 2001) are employed as the second forecasting method in this study. In BT, similar to RF, an ensemble of trees is grown over samples, but unlike RF, trees are not independent from each other and the whole train dataset is used for learning, rather than bootstrapped samples. Each tree is grown sequentially by using cumulative information (loss function) of previous trees. Typical loss function in regression setting is squared error and trees are fit to the residuals from the model, rather than actual response values. Throughout the learning, residuals are updated (by a learning rate) and used as new response values to grow the next tree. The process terminates after a predetermined condition is met. By using all the trees' knowledge, a final prediction is made[4].

Apart from their prediction performances, both RF and BT can provide valuable information on the relationship between predictors and response, which is called the variable importance. The importance of a variable is measured by the loss of performance (as increase in prediction error) when it is excluded from the model. Of course, this importance cannot be interpreted as a causal effect, but still exhibits an opportunity to understand and interpret the underlying nature of acquired results. After the most important variables are identified, their marginal effects (by integrating out other variables) on the NPL are also examined by partial dependence plots.

Both RF and BT models are implemented in R statistical software (R Core Team, 2020) by using the *randomForest* package (Liaw & Wiener, 2002) and the *gbm* package (Greenwell, Boehmke, Cunningham, & GBM Developers, 2020), respectively. All packages and codes for replication are provided in the supplementary materials.

Parameter Settings

Three parameters need to be specified for RF and BT models. Some of these parameters have major influences over performances, so it is particularly important to determine an efficient setting. This is not an easy task, and highly depends on the analyzed problem/dataset.

4 At initial step, mean of response values is used for calculating first set of residuals of all observations, then a tree is fit using this first set of residuals and predicted residuals are added to mean of response to obtain first step's predictions. These predictions are used for calculating second set of residuals of all observations and the process continues.

There are several traditional preferences in the literature; but the best approach is to tune those parameters within an experimental design. For all parameters, a range is determined and values within the range are divided with equal intervals. Then, each value of each parameter is tested while holding the remaining parameters constant. The parameter tuning design for both models is given in Table 1.

Table 1
Parameter tuning design for random forest and boosted trees models

	Parameter 1	**Parameter 2**	**Parameter 3**
	Total number of trees	*Each tree's depth*	*Number of candidate variables at each split*
Random Forest	[1, 10]; increments: 1 [100, 500]; increments: 100	[1,15]; increments: 1	[1:S*]; increments: 1
	Total number of trees	*Shrinkage parameter*	*Interaction depth*
Boosted Trees	[1, 10]; increments: 1 [100, 500]; increments: 100	[0.01,0.1]; increments: 0.01	[1:5]; increments: 1

**S = floor(number of determinants in the model / 2), 24 max.*
Note: For random forest model, number of trials starts from 1,200 (10x15x8) to 3,600 (10x10x24) and for all boosted model, there are 500 trials (10x10x5).
Source: Authors' compilation

The total number of trees depicts the number of trees to be created in each training process. Trees' depth has a direct effect on the variance-bias trade-off[5], a low (high) depth may result in a lower (higher) variance but more (less) bias on estimations. Though this trade-off can be mitigated if models include enough trees, it is still beneficial to see how model behavior changes with varying depth. The shrinkage parameter determines BT's rate of learning, which directly affects under/overfitting. Learning must be done slow enough to avoid overfitting. The number of candidate variables to be considered at each split indicates how many randomly selected variables will be used in each data space split. By not considering all the determinant variables, it becomes possible to get over a strong predictor (if any) in the data set. Eventually, more information can be gathered, and minor relationships will be revealed. Lastly, interaction depth in BT limits the total number of splits in each tree, thus related to the complexity of the trees and as in tree depth parameter of RF, variance-bias tradeoff. The subsample size in training processes in models is another parameter to tune, but as Scornet (2018) remarked, there is no need to optimize both the subsample size and the tree complexity.

Performance Estimation Method and Procedure

An unbiased model needs to perform similarly both on training data (data which is used for model building) and unseen (test) data; also called the generalization ability of the model. It is not possible to assess this ability if all observations are used for training, some must be left out for testing. In this study, some part of the dataset is used for training and the rest is

5 A recent discussion on variance-bias trade-off in machine learning can be found in (Belkin et al., 2019).

used for testing. No observations from the latter part will be used in training. The performance of training part is evaluated by an estimation method independently, and the estimation method's outcome is later compared with the test performance[6]. A comparison procedure is followed as in Cerqueira et al. (2020), and visualized in Figure 2.

For each parameter combination, a repeated holdout (Rep-hold) is used to evaluate predictive performances[7]. First, the whole data set is divided into an estimation set (70% of observations) and a validation (remaining observations) set. The estimation set is then split into 10 randomly generated holdout sets (each with a 70% of estimation set) with consecutive observations. Within each holdout set, 85% of observations are used for training and 15% left for testing. The same randomly generated holdout sets are created for each parameter set to control the sampling effect on performances. One iteration of the rep-hold method is shown in Figure 3. This procedure is also followed for obtaining the CART benchmark model's performance.

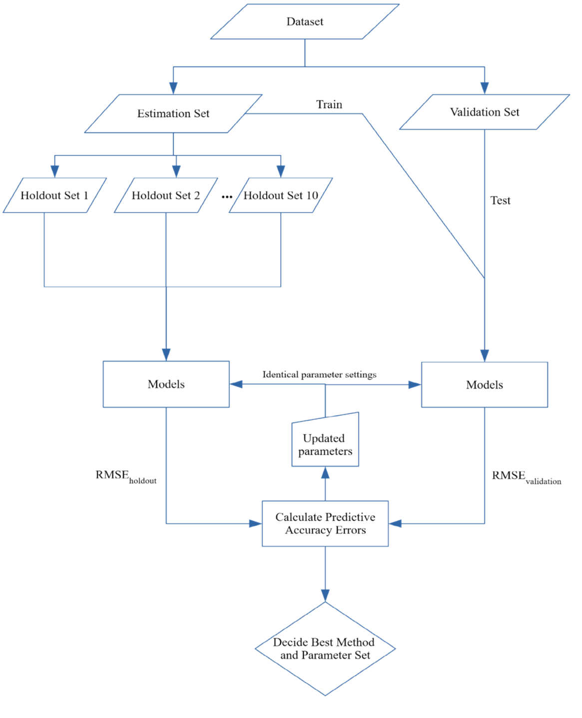

Figure 2. Flow of model evaluation and parameter selection

Source: Authors' compilation

6 Details on performance evaluation metrics are given in Section 4.5

7 Among many other alternatives, rep-hold is seen more suitable in case of non-stationary time series analyses (Cerqueira et al., 2020).

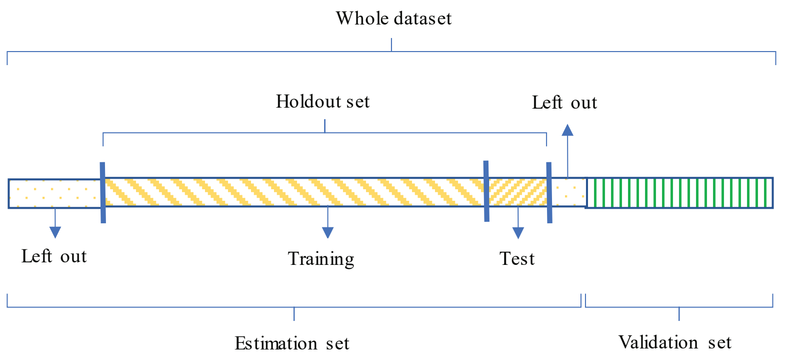

Figure 3. An example to one iteration of repeated holdout validation

Source: Authors' compilation

Evaluation Metrics

The models' performances are evaluated according to the root-mean square error (RMSE) and the mean absolute error (MAE) metrics, calculated as in equations 1 and 2:

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(e_n)^2}{N}} \tag{1}$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|e_n| \tag{2}$$

where e_n is the difference (error) between the predicted value ($\hat{p}_n$) and the actual value (p_n) of n^{th} test observation, and N is the total number of test observations.

RMSE is a standard metric commonly used in literature but there is a debate on its validity, such that Willmott and Matsuura (2005) proposed not to use it in studies and instead suggested to use MAE. But as Chai and Draxler (2014) presents, it is not suitable to ignore RMSE totally, even in many cases it is more reliable than MAE. Cognizant of both ideas, model selection and comparison are primarily made on RMSE but MAEs of superior models are also given.

Both the RF and BT methods are subject to randomness during training. To obtain overall performances and even explore how models react to this randomness, the methods are run 100 times (as Monte Carlo simulations) with each holdout set and with estimation set simultaneously in each parameter combination. All predictions are stored. The same random number seed is used initially, so it is possible to replicate results.

By using those simulations results, RMSE for rep-hold ($RMSE_{holdout}$) and RMSE for the validation set ($RMSE_{validation}$) are calculated as shown in Figure 4 with equations 3, 4 and 5:

$$Mean\ squared\ error\ (MSE) = \frac{\sum_{n=1}^{N}(e_n)^2}{N} \tag{3}$$

$$MSE_s = \frac{\sum_{sim=1}^{SIM} MSE_{sim}}{SIM}, \forall\ s = 1, \ldots, S \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{s=1}^{S} MSE_s}{S}} \tag{5}$$

where SIM is the total number of simulations (selected as 100) and S is the total number of holdout sets (which is 10).

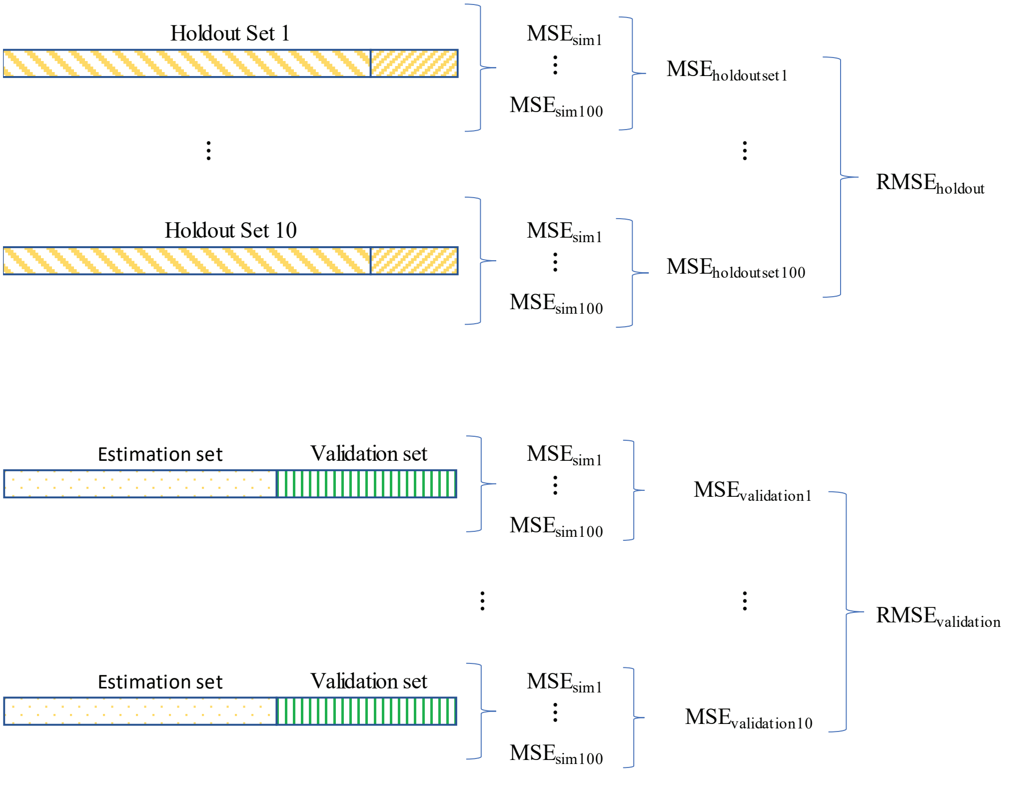

Figure 4. RMSE Calculation steps for repeated holdout and validation sets

Source: Authors' compilation

Hereinbefore mentioned, to decide if a model is reliable on future forecasts, depending solely on $RMSE_{holdout}$ or $RMSE_{validation}$ will not be enough. Therefore, another metric is used to understand how well a model's estimated error approximates truth error (Bergmeir, Hyndman, & Koo, 2018), named the absolute predictive accuracy error (APAE):

$$APAE = |RMSE_{holdout} - RMSE_{validation}| \quad (6)$$

Models that satisfy lower APAE are therefore regarded as less biased. Even in cases that RMSEs on validation set are higher than competitive models, the generalization ability of models with low APAE is considered more robust. So, in this study, parameters that give the lowest APAE are selected as the best.

Results

Optimum Parameters

For all lag specifications, the best parameter sets that provide APAE in RF and BT models are given in Table 2 and Table 3, respectively. RMSEs of the validation set and the CART model APAE are also given.

Table 2

Optimum Set of Parameters for Each Lag Specification, Random Forest

Included lags	Total number of trees	Each tree's depth	Number of candidate variables at each split	Baseline APAE	APAE	Validation set RMSE
1	300	1	1	0.0671	0.0339	2.1267
2	10	8	5	0.4924	0.0001	1.0993
3	1	4	8	0.3449	0.0029	1.4337
4	1	8	2	0.2591	0.4331	1.3047
1, 2	500	4	15	0.0216	0.0000	0.9442
1, 2, 3	6	2	24	0.0686	0.0000	1.2073
1, 2, 3, 4	1	9	15	0.2802	0.0014	1.3887

Source: Authors' compilation. Results obtained from R output.

Table 3

Optimum Set of Parameters for Each Lag Specification, Boosted Tree

Included lags	Total number of trees	Learning rate	Total number of splits at each tree	Baseline APAE	APAE	Validation set RMSE
1	1	0.07	3	0.0671	0.0000	1.9982
2	200	0.08	1	0.4924	0.0091	0.7867
3	2	0.05	1	0.3449	0.3392	1.4423
4	1	0.01	1	0.2591	0.4391	1.2980
1, 2	400	0.01	2	0.0216	0.0000	0.9489
1, 2, 3	500	0.06	3	0.0686	0.0003	0.6416
1, 2, 3, 4	400	0.1	1	0.2802	0.0671	0.6369

Source: Authors' compilation. Results obtained from R output.

Both RF and BT overperformed the baseline model. The best APAE was achieved when only the first lag was included and the first and second lags of predictors are included in BT. Latter specification provides a better validation set RMSE. Two specifications compete in RF also: Two lags with intermediate periods or three lags with intermediate periods. The former specification is also best for the validation set RMSE in RF. Adding more lags to the models seem not to supply extra valuable information for learning, and may even worsen model success.

NPL Ratio Forecasts

The validation (out-of-sample) part of the dataset covers the period 2015:Q1 and 2019:Q4. In Figure 5, mean random forest (model with first and second lags included and with optimum parameter set in Table 2) forecasts are given along with the boxplots.

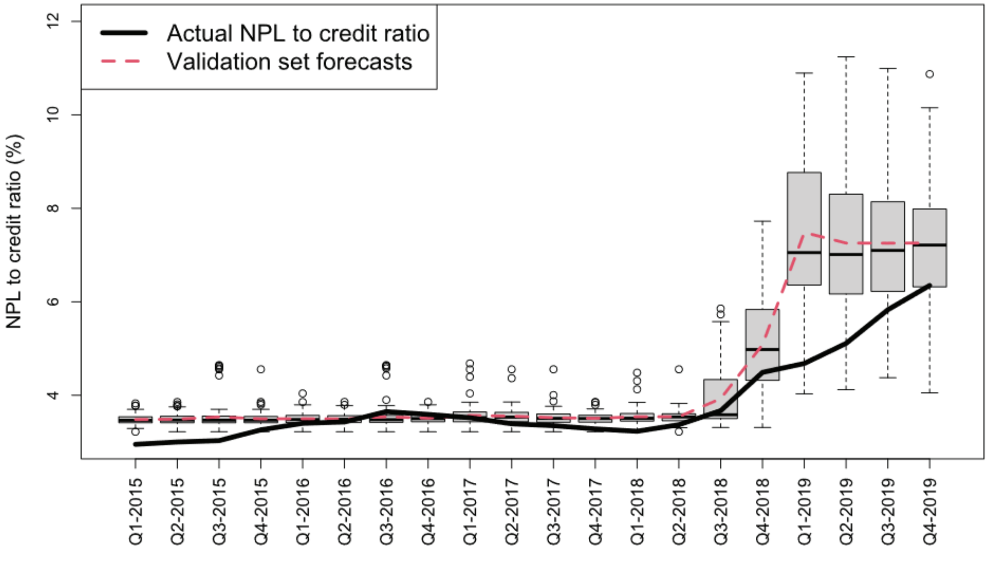

Figure 5. Random forest forecasts, boxplots are created with 100 simulations. RMSE = 1.1692, MAE = 0.6429
Source: Results obtained from R output. Plotted in RStudio

The model provides very good forecasts for four years within the validation period, closely follows true NPL ratios and reacts to trend changes[8]. During 2019, the forecast errors dramatically increase[9], and RF starts to overestimate the NPL ratio (although the gap closes in the last quarter of 2019). Additionally, the distribution of forecasts widens, and some outliers are seen above.

8 Pearson correlation between forecast and actual values = 0.9239, p-value < 0.05.

9 Pearson correlation between forecast and actual values = -0.3516, p-value = 0.6484.

In Figure 6, BT forecasts are given (with the first and second lags included and with the optimum parameter set in Table 3), which are pretty much similar to the RF forecasts. Again, the model starts to overestimate the true NPL ratios after 2019:Q1[10]. In 2019:Q4, the BT forecast is more closer to the true NPL ratio than the RF forecast. As RMSE and MAE suggests, BT overperforms RF by a small difference.

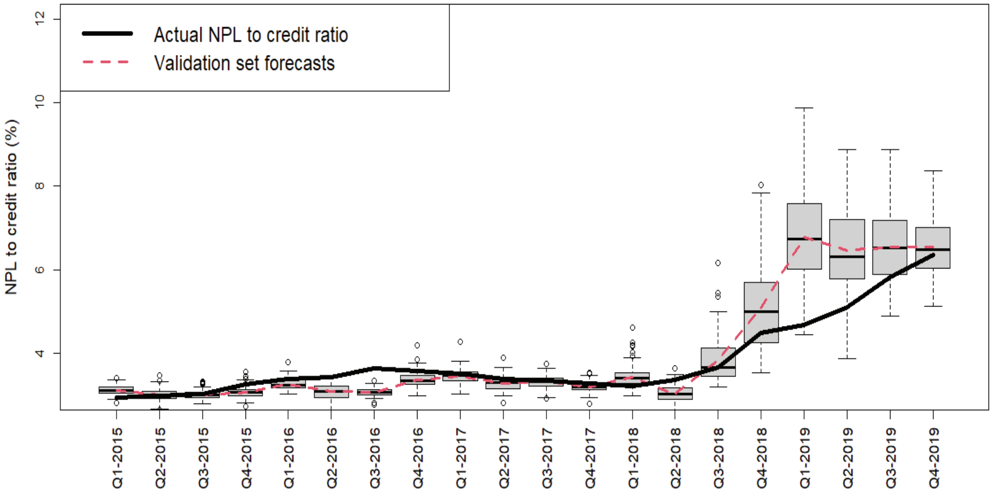

Figure 6. Boosted tree forecasts, boxplots are created with 100 simulations. RMSE = 0.6073, MAE = 0.3368
Source: Results obtained from R output. Plotted in RStudio

Overall, both models are found to be successful for tracking NPL ratios until 2019; the underlying reason(s) is going to be discussed in Section 6.

Predictor Importance

The previous quarter's NPL ratio (NPLL1) is explicitly the superior predictor of the NPL ratio in both models. The following important predictors are similar but there are some differences in their ranks. By consulting the mean importance metric for RF, the order of the most distinguished importance continues after NPLL1 as NPLL2, CreditL2, InflationL2, InterestL2, CreditL1, InterestL1, InflationL1 and CAdequacyL1 (see Figure 7). For BT, again by consulting the mean importance metric, the importance order after NPLL1 occurs as InterestL1, InflationL1, CAdequacyL1, NPLL2, InterestL2, CreditL1, InflationL2 (see Figure 8). As is seen, factors from both bank-specific and macroeconomic categories are found informative.

10 Pearson correlation between 2015:Q1 and 2018:Q4 is 0.8709, p-value < 0.05. Pearson correlation between 2019:Q1 and 2019:Q4 is 0.3762, p-value = 0.6238.

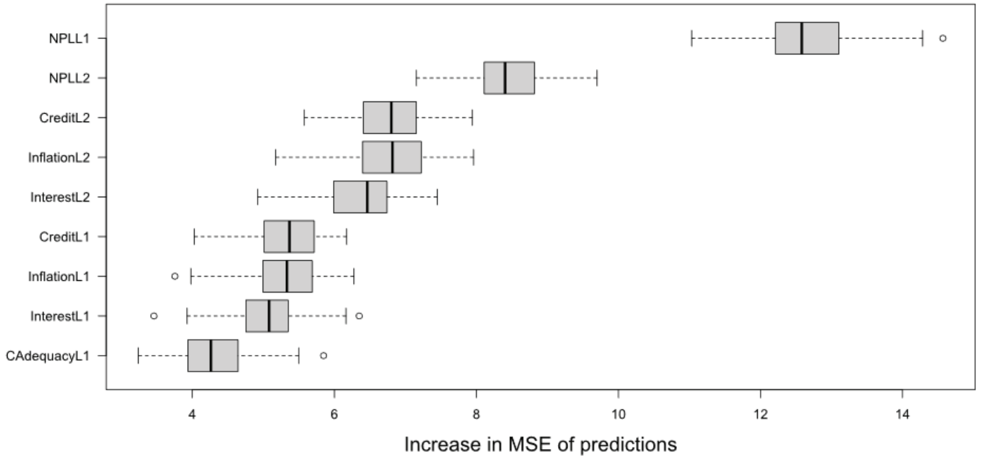

Figure 7. Boxplots of variable importance (100 simulations), random forest method. Outliers are shown as circles

Source: Results obtained from R output. Plotted in RStudio

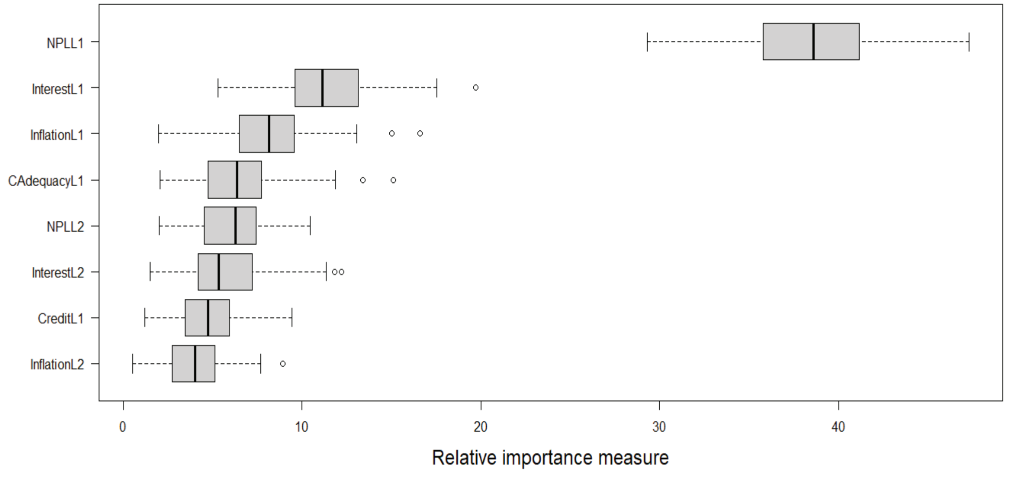

Figure 8. Boxplots of relative variable importance (100 simulations) boosted tree method. Outliers are shown as circles

Source: Results obtained from R output. Plotted in RStudio

Discussion and Policy Recommendations

In this study, NPL ratios in Turkey are forecasted by using two methods: random forests and boosted trees. Data starting from 2003:Q1 until 2014:Q4 are used for training and 2015:Q1 to 2019:Q4 are used for forecasting. In both methods, the same set of variables is used. Variables are selected in conjunction with the prior studies on NPLs in the literature. Some uncertainty measures are also included.

To evaluate the generalization ability of methods, an absolute predictive accuracy error metric is used. The root mean squared error metric is further used to see the model's forecasting performance. Both employed methods perform similarly in terms of both metrics. It is found that the first (one quarter earlier) and second lags (two quarters earlier) of variables provide the best forecasting results. When intermediate lags are excluded, the third and fourth lags do not provide adequate information on future NPL ratios. Therefore, it is possible to say variable influences on future NPL ratios have a short-term memory. Even any causal relationships cannot be inferred with the employed approach, results indicate that several variables are highly informative.

The variables' importance reveals that the NPL ratio has an autoregressive structure. The most influential variable on future NPL ratios is the NPL ratio itself, with one and two lags, and has an increasing effect (see Figure 9 and Figure 10). This is in line with the findings of Makri et al. (2014) and Arrawatia et al. (2019). From the policy-making or regulatory perspective, focusing on dealing with current problematic loans will be more beneficial for the system in the short-term. Turkey has several experiences in restructuring loans, i.e., the Istanbul Approach in 2002 and the Anadolu Approach in 2006. While both approaches are not considered as perfectly effective, it is evident that there is a need for better management of current problematic loans.

More recent changes/regulations, starting from August 2018 seem to mitigate problems to some extent. The big difference between this study's forecasts and NPL ratios in 2019 gives us some clues. Particularly good forecasts prior to 2019 and the sudden decline in forecasting performance after, provides valid reasons to believe that the banking system would be exposed to higher volumes of problematic loans in Turkey after 2019. The methods' forecasts converge to actual ratios at the end of 2019.

To explain this more specifically, it is necessary to track recent regulations. Debt restructuring was introduced in Turkey after the currency crises in 2018 and is defined in the law; as granting a new loan to a debtor who is in difficulty or likely to be in difficulty to pay the current loan, in order to ensure total or partial payment. It is also expected to enable banks and other financial institutions to facilitate a uniform approach regarding the NPLs portfolio. At end of January 2019, 336 large-scale firms applied for the debt restructuring and 163 firms' processes were completed (The Banks Association of Turkey, 2019). Depending on these regulations, maturities of loans are extended, new loans are provided by the lenders and the loans which should be transferred as NPLs were not transferred. These restructured loans are classified as under performing loans instead of a NPL.

Partial dependencies reveal that inflation, interest rate and capital adequacy ratios have a positive relationship with NPL ratios for both the first and second lags, though these relationships are not same for all ranges. As an example, consider the functional relationship of the first lag of inflation with NPL ratios; in both Figure 9 and Figure 10, the marginal effect of inflation is nearly zero up to two digits inflation rates, and a sudden increase is seen after, which is again followed by a zero-marginal effect. Moreover, it is important to note that these bilateral relationships are assumed to be independent from other predictors' influences, which cannot be considered as a valid assumption, especially in this analysis. But still, they provide an insight.

A positive relationship of inflation with NPLs is also reported by Nkusu (2011), Louzis et al. (2012), Messai and Jouini (2013), Arrawatia et al. (2019). But there are different views about inflation's effect on NPLs; it may be an advantage for borrowers by reducing the debt's real value, or it may deteriorate the repayment capacity by reducing the real income. For Turkey, Vatansever and Hepsen (2013), Khan et al. (2018) and Kılıç and Kartal (2021)[11] found inflation is not significant. This study's finding is in line with Us (2018).

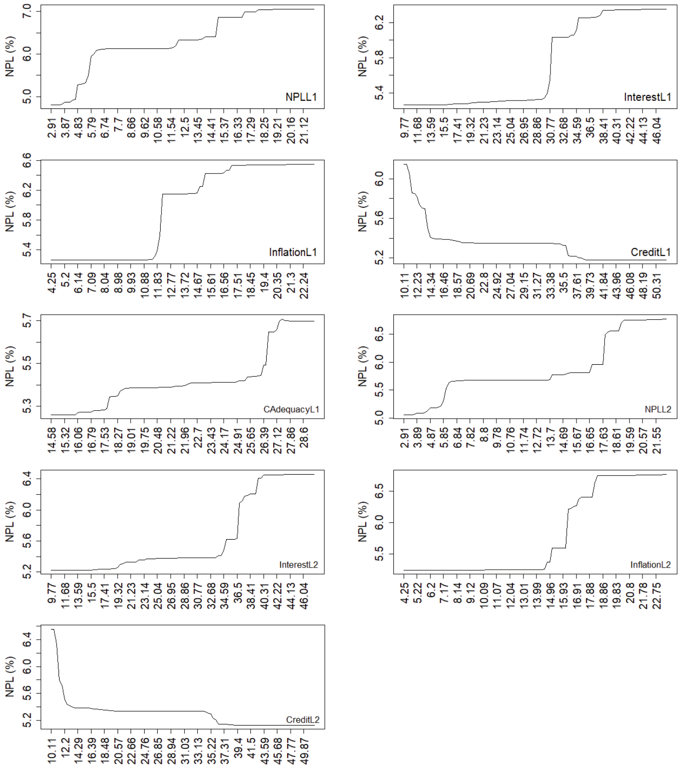

Figure 9. Partial dependency plots of most important variables, random forest

Source: Results obtained from R output. Plotted in RStudio

11 In this study, producer price index is found to be reversely related with NPL.

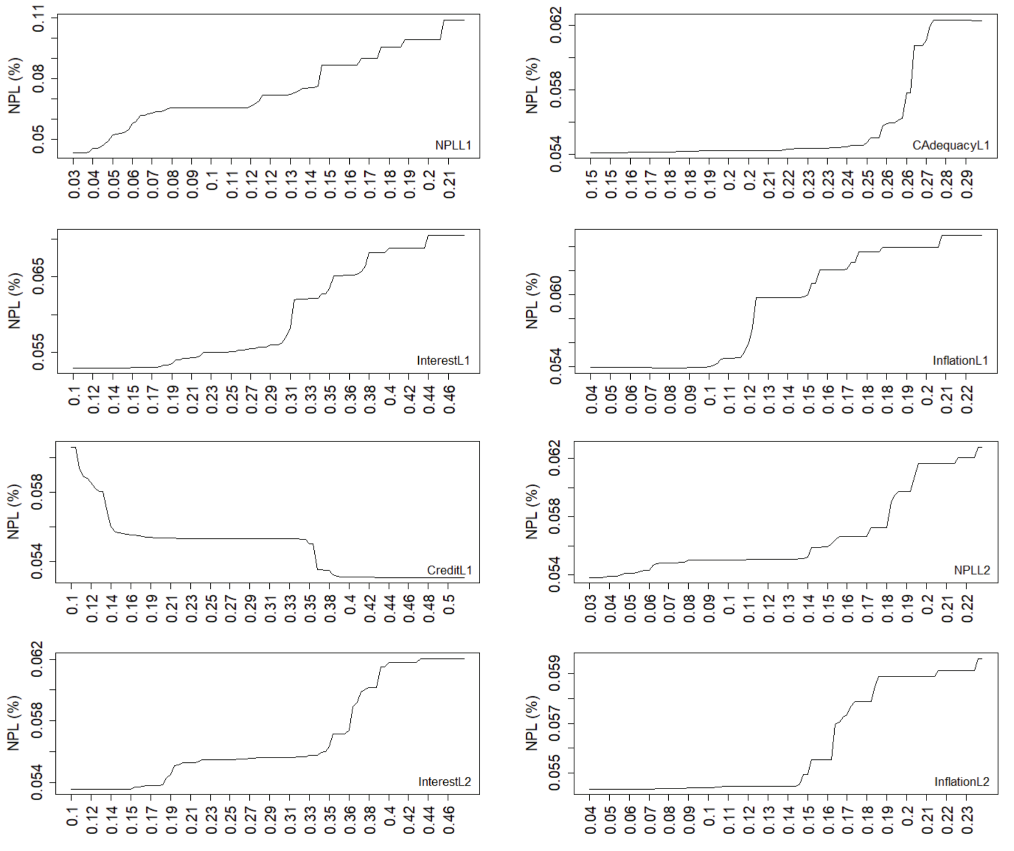

Figure 10. Partial dependency plots of most important variables, boosted tree
Source: Results obtained from R output. Plotted in RStudio

In Turkey, a positive link with capital adequacy and the NPL ratio is also documented in Us (2018) (for the period 2002:Q4 and 2015:Q4). Kılıç and Kartal (2021) agree that for the NPL volume (2005-2019 period). One may argue banks with highly adequate capital positions may be more willing to accept riskier loans. Also, the interest rate and NPL relationship found in this study is consistent with Kılıç and Kartal (2021). The credit amount compared to GDP in the economy has a negative relationship with the NPL ratio; which will contribute to the adoption of extensive macroprudential measures (Us, 2018: 1614). NPL reduction could free up a sizeable amount of loanable funds and cyclically help to improve the financial structure of corporate sector in Turkey.

Concluding Remarks

As a conclusion, this study's methods are believed to be useful for successfully predicting future NPL ratios in Turkey (but also applicable for other country analyses), and thus may be beneficial to the financial sector and market regulators.

It is also important to note that there are possible events/times that altered dynamics of NPLs; global events like the 2008 Financial Crisis or local events like the coup attempt in 2016. Continuing studies incorporating such significant changes will be insightful. A comprehensive approach to manage the economic and institutional situation can lead to a more sustainable lending environment and eventually result in better economic conditions. The current pandemic's influence on problematic loans is also worth examining, but it is left for future studies.

Supplementary materials

Dataset, information on data, preliminary analyses results and codes can be found in:

https://data.mendeley.com/datasets/vz758vy3yr/draft?a=2aff80b3-96a7-41fe-82b8-438c27fae8de

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References

Aiyar, M. S., Bergthaler, M. W., Garrido, J. M., Ilyina, M. A., Jobst, A., Kang, M. K., … Moretti, M. M. (2015). *A strategy for resolving Europe's problem loans*. International Monetary Fund.

Altınbaş, H. (2020). Modern kredi sınıflandırma çalışmaları ve metasezgisel algoritma uygulamaları: Sistematik bir derleme (Metaheuristic algorithms and modern credit classification methods: A systematic review). *Istanbul Business Research*, *49*(1), 146–175. https://doi.org/10.26650/ibr.2020.49.0033

Arrawatia, R., Dawar, V., Maitra, D., & Dash, S. R. (2019). Asset quality determinants of Indian banks: Empirical evidence and policy issues. *Journal of Public Affairs*, *19*(4), e1937.

Balgova, M., Nies, M., & Plekhanov, A. (2016). *The economic impact of reducing non-performing loans*.

Banking Regulation and Supervision Agency of Turkey. (2019). *Turkish Banking Sector Main Indicators*.

Bellotti, A., Brigo, D., Gambetti, P., & Vrins, F. (2021). Forecasting recovery rates on non-performing loans with machine learning. *International Journal of Forecasting*, *37*(1), 428–444.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870.

Bergmeir, C., Hyndman, R. J., & Koo, B. (2018). A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics and Data Analysis*, *120*, 70–83. https://doi.org/10.1016/j.csda.2017.11.003

Boudriga, A., Taktak, N. B., & Jellouli, S. (2009). Banking supervision and nonperforming loans: a cross-country analysis. *Journal of Financial Economic Policy*.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Cerqueira, V., Torgo, L., & Mozetič, I. (2020). Evaluating time series forecasting models: an empirical study on performance estimation methods. *Machine Learning*, *109*(11), 1997–2028. https://doi.org/10.1007/s10994-020-05910-7

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, *7*(3), 1247–1250. https://doi.org/10.5194/gmd-7-1247-2014

Changqing Cheng, Akkarapol Sa-Ngasoongsong, Omer Beyca, Trung Le, Hui Yang, Zhenyu (James) Kong & Satish T.S. Bukkapatnam (2015) Time series forecasting for nonlinear and non-stationary processes: a review and comparative study, IIE Transactions, 47:10, 1053-1071, DOI: 10.1080/0740817X.2014.999180

Dimitrios, A., Helen, L., & Mike, T. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters*, *18*, 116–119. https://doi.org/10.1016/j.frl.2016.04.008

European Central Bank Banking Supervision. (2017). *Guidance to banks on non-performing loans*.

Finansal Yeniden Yapılandırma Koordinasyon Sekreteryası. (2005). *İstanbul yaklaşımı: Bir yeniden yapılandırma deneyimi (Istanbul approach: A restructuring experience)*.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232.

Gormez, Y. (2008). *Banking in Turkey: history and evolution*.

Greenidge, K., & Grosvenor, T. (2010). Forcasting non-performing loans in Barbados. *Journal of Business, Finance & Economics in Emerging Economies*, *5*(1).

Greenwell, B., Boehmke, B., Cunningham, J., & GBM Developers. (2020). *gbm: Generalized boosted regression models*.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (Second). Springer Science & Business Media.Khan, I., Ahmad, A., Khan, M. T., & Ilyas, M. (2018). The impact of GDP, inflation, exchange rate, unemployment and tax rate on the non performing loans of banks: Evidence from Pakistani commercial banks. *Journal of Social Sciences and Humanities*, *26*(1).

Kılıç Depren, S., & Kartal, M. T. (2021). Prediction on the volume of non-performing loans in Turkey using multivariate adaptive regression splines approach. International Journal of Finance & Economics, 26(4), 6395-6405.

Kjosevski, J., Petkovski, M., & Naumovska, E. (2019). Bank-specific and macroeconomic determinants of non-performing loans in the Republic of Macedonia: Comparative analysis of enterprise and household NPLs. *Economic Research-Ekonomska Istraživanja*, *32*(1), 1185–1203.

Kozarić, K., & Žunić, E. (2015). Causes and consequences of NPLs in Bosnia and Herzegovina banking sector. *Journal of Economic and Social Studies, 5*(1), 127-144

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling* (26th ed.). New York: Springer.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, *2*(3), 18–22. https://doi.org/10.1023/A:1010933404324

López De Prado, M. (2018). The 10 Reasons Most Machine Learning Funds Fail. *The Journal of Portfolio Management*, *44*(6), 120–133. Retrieved from www.TruePositive.com

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.

Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, *61*(2), 193–206. https://doi.org/10.2298/PAN1402193M

Messai, A. S., & Jouini, F. (2013). Micro and Macro Determinants of Non-performing Loans. *International Journal of Economics and Financial Issues*, *3*(4), 852–860. Retrieved from www.econjournals.com

Mishkin, F. S. (2007). *The economics of money, banking, and financial markets*. Pearson education.

Munteanu, I. (2012). Bank Liquidity and its Determinants in Romania. *Emerging Market Queries in Finance and Business*, 993-998.

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Papers*, 1–27.

Orhangazi, Ö. (2014). Capital flows and credit expansions in Turkey. *Review of Radical Political Economics*, *46*(4), 509–516.

Ozatay, F., & Sak, G. (2002). Banking sector fragility and Turkey's 2000-01 financial crisis. *Brookings Trade Forum*, *2002*(1), 121–160.

Ozili, P. K. (2019). Non-performing loans and financial development: new evidence. *The Journal of Risk Finance*.

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, *4*(2), 135–148.

Poudel, R. P. S. (2012). The impact of credit risk management on financial performance of commercial banks in Nepal. *International Journal of Arts and Commerce*, *1*(5), 9–15.

R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American Economic Review*, *101*(5), 1676–1706.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*(3), 203–224.

Scornet, E. (2018). Tuning parameters in random forests. *ESAIM: Proceedings and Surveys*, *60*, 144–162. EDP Sciences. https://doi.org/10.1051/proc/201760144

The Banks Association of Turkey. (2019). Framework agreements on financial restructuring. Retrieved January 17, 2021, from https://www.tbb.org.tr/en/banking-legislation/professional-codes-/framework-agreements-on-financial-restructuring/91

The European Systemic Risk Board. (2019). *Macroprudential approaches to non-performing loans*.

Us, V. (2018). The determinants of nonperforming loans before and after the crisis: Challenges and policy implications for Turkish banks. *Emerging Markets Finance and Trade*, *54*(7), 1608–1622.

Vatansever, M., & Hepsen, A. (2013). Determining impacts on non-performing loan ratio in Turkey. *Journal of Finance and Investment Analysis*, *2*(4), 119–129.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82. Retrieved from www.int-res.com

Woo, D. (2000). *Two approaches to resolving nonperforming assets during financial crises*.

Yentürk, N. (1999). Short-term capital inflows and their impact on macroeconomic structure: Turkey in the 1990s. *The Developing Economies*, *37*(1), 89–113.