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FORECASTING NPL OF COMMERCIAL BANKS IN UZBEKISTAN USING VAR MODEL

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Abstract
This study examines the forecasting of non-performing loans (NPL) in Uzbekistan's banking sector by focusing on key macroeconomic indicators — GDP growth, interest rate, exchange rate, and inflation rate. I analyze monthly data from March 2020 to October 2024 by employing a Vector Autoregressive (VAR) model to capture the dynamic relationships between endogenous variables. The findings suggest that lagged GDP growth and interest rate have a significant positive association with the NPL rate, reflecting delayed effects of economic growth and borrowing costs on loan performance. The VAR model's predictive accuracy was validated against historical data, and future forecasts for the next six months were generated with a 60% prediction interval.
Keywords: non-performing loans, NPL, VAR, GDP growth

Annotatsiya
Ushbu tadqiqot O'zbekiston bank tizimidagi muammoli kreditlar (NPL) prognozini makroiqtisodiy asosiy ko'rsatkichlar — YIM o'sishi, foiz stavkasi, valyuta kursi va inflyatsiya darajasi orqali o'rganadi. Men 2020 yil martdan 2024 yil oktyabrgacha bo'lgan oylik ma'lumotlarni tahlil qilib, endogen o'zgaruvchilar o'rtasidagi dinamik aloqalarni aniqlash uchun Vektor Avto Regressiya (VAR) modelidan foydalanaman. Natijalar shuni ko'rsatadiki, kechiktirilgan YIM o'sishi va foiz stavkasi NPL darajasi bilan ijobiy va sezilarli aloqaga ega bo'lib, bu iqtisodiy o'sish va qarz olish xarajatlarining kreditlar samaradorligiga kechikkan ta'sirlarini aks ettiradi. VAR modelining prognozlash aniqligi tarixiy ma'lumotlar asosida tasdiqlandi va kelgusi olti oy uchun prognozlar 60% prognoz oralig’i bilan ishlab chiqildi.

Аннотация
Настоящее исследование посвящено прогнозированию уровня проблемных кредитов (NPL) в банковском секторе Узбекистана с фокусом на ключевые макроэкономические показатели — рост ВВП, процентную ставку, курс обмена и уровень инфляции. Я анализирую месячные данные с марта 2020 года по октябрь 2024 года, используя модель векторной авторегрессии (VAR) для выявления динамических взаимосвязей между эндогенными переменными. Результаты показывают, что запаздывающий рост ВВП и процентная ставка имеют значительную положительную связь с уровнем NPL, отражая запаздывающие эффекты экономического роста и стоимости заимствования на эффективность кредитования. Прогностическая точность модели

VAR была подтверждена на основе исторических данных, и были сгенерированы прогнозы на следующие шесть месяцев с интервалом прогнозирования 60%.

Introduction

Non-performing loans (NPL) is a key indicator of the quality of lending institutions’ (i.e. commercial banks and/or non-bank lenders) assets and the health of the financial system in the country. Currently, high interest rates and the resulting debt servicing stress for borrowers means that forecasting NPL is important for understanding the potential impacts on the financial system. In general, NPL ratios are affected by the state of the economy. Borrowers may experience financial difficulties as a result of higher interest rates, which may compel them to reduce discretionary spending or seek to work more hours. In a similar way, a decline in economic activity that lowers company revenue could potentially limit profit margins and deplete cash reserves. Temporary support measures offered by their lending institutions, such as extending the loan's term or reducing principal and interest payments to just interest, might not be enough to keep the borrower from missing required repayments if these deteriorations continued, ultimately leading to the loan becoming non-performing.

For the banking industry to effectively manage risk, NPL forecasting accuracy is crucial. Banks can better plan for possible loan defaults and modify their capital adequacy requirements, lending policies, and provisioning procedures by forecasting future patterns in non-performing loans. Financial authorities can also evaluate the general state of the banking industry and take prompt action to protect the stability of the financial system by forecasting non-performing loans.

Given the complexities of loan default dynamics and the relationship between macroeconomic variables and financial stability, understanding the factors that drive NPL important. Macroeconomic indicators such as GDP growth, interest rate, exchange rate, and inflation have long been recognized as key determinants of loan performance. These variables influence borrowers' ability to repay loans and can act as leading indicators of changes in NPL levels. As such, using these macroeconomic factors to forecast NPL is an important area of research, particularly in emerging economies where economic volatility can have a more pronounced effect on the financial system.

Literature Review

There are many empirical studies that have assessed the relationship between NPL share and key macroeconomic indicators, such as GDP growth, (un)employment rate, inflation rate, exchange rate, equity index and housing prices. [1] suggest that non-performing loans (NPLs) can serve as indicators signaling the beginning of a banking crisis. [2] analyze the sample of European countries and report that disposable income, unemployment and monetary conditions have significant impact on NPL. [3] analyze Nordic banks between 1993 – 2005 and conclude that troubled loans are highly sensitive to the real interest rates and unemployment rate. The NPL ratio increases as economic growth slows and interest rates rise [4] who estimated a dynamic panel over 1995–2008 on a sample of about 80 banks in the Gulf Cooperation Council region. According to these authors countries featuring a relatively high

portion of private sector borrowing in foreign currency, a significant depreciation of the local currency may lead to a considerable increase in NPLs through the balance sheet channel.

[5] have studied 75 countries for a decade on dynamic panel estimates and have reported that exchange rate depreciations might lead to an increase of non-performing loans in countries with a high degree of lending in foreign currencies to unhedged borrowers. On the other hand, [6] has found positive relationship between these two variables. This author explains this tendency by competitiveness channel which refers to improved export competitiveness because of depreciation of national currency.

[7] have examined which macroeconomic and bank-level components influence the NPL of Armenian banks while comparing their results with US banking industry. They have reported negative relationship between consumer price index and NPL, and positive relationship between unemployment, exchange rate and NPL rate. In panel regressions for 26 advanced economies between 1998 and 2009, [8] examines the macroeconomic factors that influence the NPL ratio. Her findings support the notion that negative macroeconomic events—specifically, a decline in real GDP, a rise in the unemployment rate, higher interest rates, a decline in home and equity prices—are linked to an increase in non-performing loans.

[9] suggest that "the GDP has a crucial deterministic role for the NPLs ratio unveiling that the state of the economy of (selected) emerging countries is linked to bank asset quality." [10] examine how macroeconomic factors affect non-performing loans and financial stability in the banking industry of Bosnia and Herzegovina. The findings indicate that when macroeconomic conditions improve, credit quality also improves.

[11] applies dynamic panel approach to determine the main factors affecting NPL of commercial banks in Uzbekistan and reports significant association between GDP growth and NPL.

Data and Methodology

This paper aims to fill the gap by forecasting the NPL rate (monthly weighted average) in the banking system of Uzbekistan using the following macroeconomic factors: GDP growth (quarterly), inflation rate (month-over-month rate), exchange rate (monthly change) and interest rate (monthly weighted average). While doing so, an interval-based approach is utilized in forecasting NPL. This method involves predicting not only a single point estimate (such as the most likely future value) but also a range of values within a specified confidence level. This range, known as the prediction interval or forecast interval, provides upper and lower bounds within which future values are likely to fall, offering insight into the degree of uncertainty surrounding the forecast.

Econometric analysis of this section includes the monthly data of NPL from March 2020 to October 2024. The descriptive statistics of the variables are given in Table 1.

To model and predict the NPL using the macroeconomic variables, this study employs Vector Autoregressive (VAR) model, which is widely used for forecasting multivariate time series data when the objective is to capture the interdependencies among multiple variables over time. It is particularly suitable in situations where the variables are endogenous (i.e., influenced by each other) and there is no need to impose a structural equation for each variable. For example, interest rate can influence GDP growth by affecting consumption and

investment. GDP growth can impact inflation rates because stronger economic growth can put upward pressure on prices. Similarly, exchange rate changes may influence inflation and interest rates through trade and monetary policy channels.

Table 1

Descriptive statistics of macroeconomic variables.

Variable	n	mean	sd	min	max
NPL	56	0.04	0.01	0.02	0.06
Interest	56	0.23	0.01	0.20	0.27
GDP	56	0.05	0.02	0.01	0.08
Exchange	56	-0.01	0.01	-0.06	0.02
Inflation	56	0.01	0.02	0.00	0.08

Given this interrelationship, a VAR model is appropriate because it allows for the modeling of these dynamic relationships without requiring a predefined causal structure. Additionally, the VAR model does not impose restrictions on the direction of causality, making it flexible and useful in capturing the feedback loops between NPL and the macroeconomic variables.

For a VAR model of order p, the following equation can be written to predict NPL:

$$NPL_t = c + \sum_{i=1}^{p} \alpha_i NPL_{t-i} + \sum_{i=1}^{p} \beta_i Interest_{t-i} + \sum_{i=1}^{p} \gamma_i GDP_{t-i} + \sum_{i=1}^{p} \delta_i Exchange_{t-i} + \sum_{i=1}^{p} \theta_i Inflation_{t-i} + \epsilon_t \quad (1)$$

In this equation:

- c is the constant term.
- $\alpha_i, \beta_i, \gamma_i, \delta_i, \theta_i$ are the coefficients to be estimated.
- ϵ_t represents the error term at time t.

Before using VAR model, we must make sure that the stationarity assumption about the variables is met. Stationarity is a key concept in time series analysis and refers to a property of a time series in which its statistical properties (like mean, variance, and autocovariance) are constant over time. A stationary time series does not exhibit trends or seasonality, and its behavior is predictable in the sense that any point in the series is similar in distribution to any other point when observed over time.

The stationarity ensures that the relationships between variables are stable over time, which is essential for making reliable forecasts. Augmented Dickey-Fuller test (ADF) has been employed to assess the stationarity of each variable and the results of Table 2 are obtained.

Since NPL, GDP and Inflation variables are not stationary, first difference is taken from all variables. After taking the first difference, our model takes the following form:

$$\Delta NPL_t = c + \sum_{i=1}^{p} \alpha_i \Delta NPL_{t-i} + \sum_{i=1}^{p} \beta_i \Delta Interest_{t-i} + \sum_{i=1}^{p} \gamma_i \Delta GDP_{t-i} + \sum_{i=1}^{p} \delta_i \Delta Exchange_{t-i} + \sum_{i=1}^{p} \theta_i \Delta Inflation_{t-i} + \epsilon_t \quad (2)$$

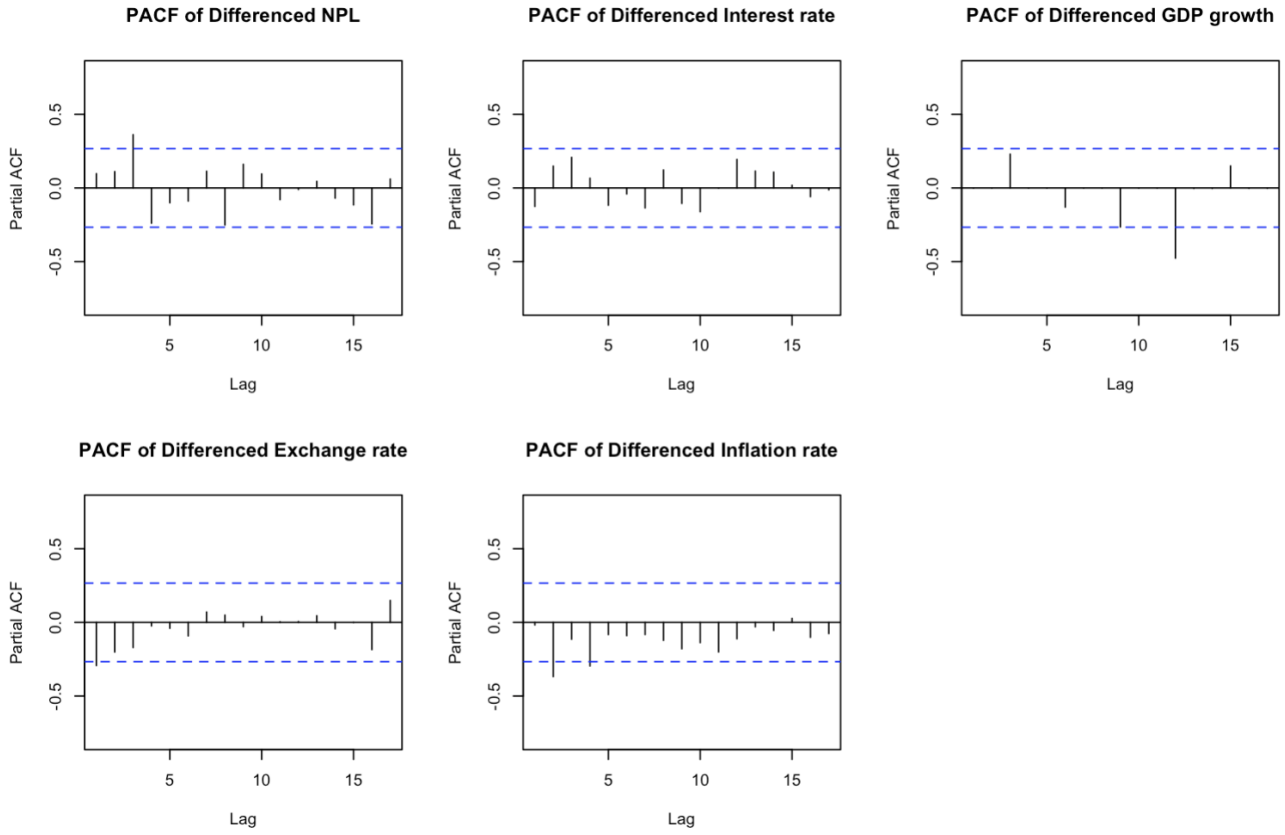
Here, Δ denotes the first difference.

Table 2

The results of Augmented Dickey-Fuller test

Variable	Dickey-Fuller	p-value
NPL	-2.41	0.41
Interest	-4.00	0.02
GDP	-2.47	0.38
Exchange	-4.28	<0.01
Inflation	-3.14	0.11

Partial Autocorrelation Function (PACF) plots given in Picture 1 do not show any significant spikes after few lags (except GDP, but it is also non-significant) and it indicates that there is no serial autocorrelation which would violate the stationarity assumption of VAR models.



Picture 1. Partial Autocorrelation Function (PACF) plots.

The results of VAR model (See Table 3) show that lags of GDP and Interest are

Table 3

VAR results

VAR Results

	Dependent variable:				
	NPL	GDP	Interest	Exchange	Inflation
NPL (L1)	0.0670	0.7273***	−0.2320	0.4299	−0.5357
	(0.1618)	(0.2653)	(0.2757)	(0.6075)	(0.5484)
GDP (L1)	0.0615	−0.2659	0.0244	0.1653	0.7819*
	(0.1147)	(0.1882)	(0.1955)	(0.4309)	(0.3890)
Interest (L1)	−0.0477	−0.2273	−0.1116	0.1163	0.8742**
	(0.0978)	(0.1604)	(0.1666)	(0.3672)	(0.3315)
Exchange (L1)	0.0170	−0.1383*	0.1083	−0.6137***	−0.0462
	(0.0432)	(0.0708)	(0.0736)	(0.1622)	(0.1464)
Inflation (L1)	0.0121	0.1182	0.0559	0.1294	0.1180
	(0.0492)	(0.0807)	(0.0839)	(0.1848)	(0.1669)
NPL (L2)	−0.1861	0.0379	−0.2726	0.8164	0.0836
	(0.1662)	(0.2725)	(0.2832)	(0.6241)	(0.5634)
GDP (L2)	0.1962*	0.3000*	−0.3569*	−0.7797*	−0.6582*
	(0.1060)	(0.1738)	(0.1806)	(0.3979)	(0.3592)
Interest (L2)	0.1973**	0.1016	0.2559	0.0856	−0.5228
	(0.0945)	(0.1549)	(0.1610)	(0.3548)	(0.3203)
Exchange (L2)	−0.0411	−0.1310	0.0021	−0.4830**	0.0352
	(0.0499)	(0.0819)	(0.0851)	(0.1874)	(0.1692)
Inflation (L2)	0.0124	0.3223***	−0.1207	−0.1187	−0.5882***
	(0.0507)	(0.0832)	(0.0864)	(0.1904)	(0.1719)
NPL (L3)	0.2479	0.1157	0.2191	0.1990	−0.4748
	(0.1602)	(0.2627)	(0.2730)	(0.6015)	(0.5431)
GDP (L3)	0.0724	0.0918	0.3015**	−0.1598	0.0324
	(0.0705)	(0.1157)	(0.1202)	(0.2649)	(0.2392)
Interest (L3)	0.0884	0.1891	0.0760	−0.2597	−0.6298**
	(0.0827)	(0.1357)	(0.1410)	(0.3107)	(0.2805)
Exchange (L3)	−0.0285	−0.0140	−0.0616	−0.3984***	−0.0519
	(0.0387)	(0.0634)	(0.0659)	(0.1452)	(0.1311)
Inflation (L3)	−0.0203	0.0787	0.1895*	0.0251	−0.2084
	(0.0548)	(0.0899)	(0.0934)	(0.2059)	(0.1859)
const	0.00001	0.0008	0.0005	0.0003	−0.000002
	(0.0005)	(0.0008)	(0.0008)	(0.0018)	(0.0016)
Observations	51	51	51	51	51
R2	0.4330	0.5742	0.3709	0.4518	0.5397
Adjusted R2	0.1901	0.3918	0.1014	0.2169	0.3425
Residual Std. Error (df = 35)	0.0033	0.0054	0.0056	0.0124	0.0112
F Statistic (df = 15; 35)	1.7822*	3.1471***	1.3760	1.9230*	2.7362***

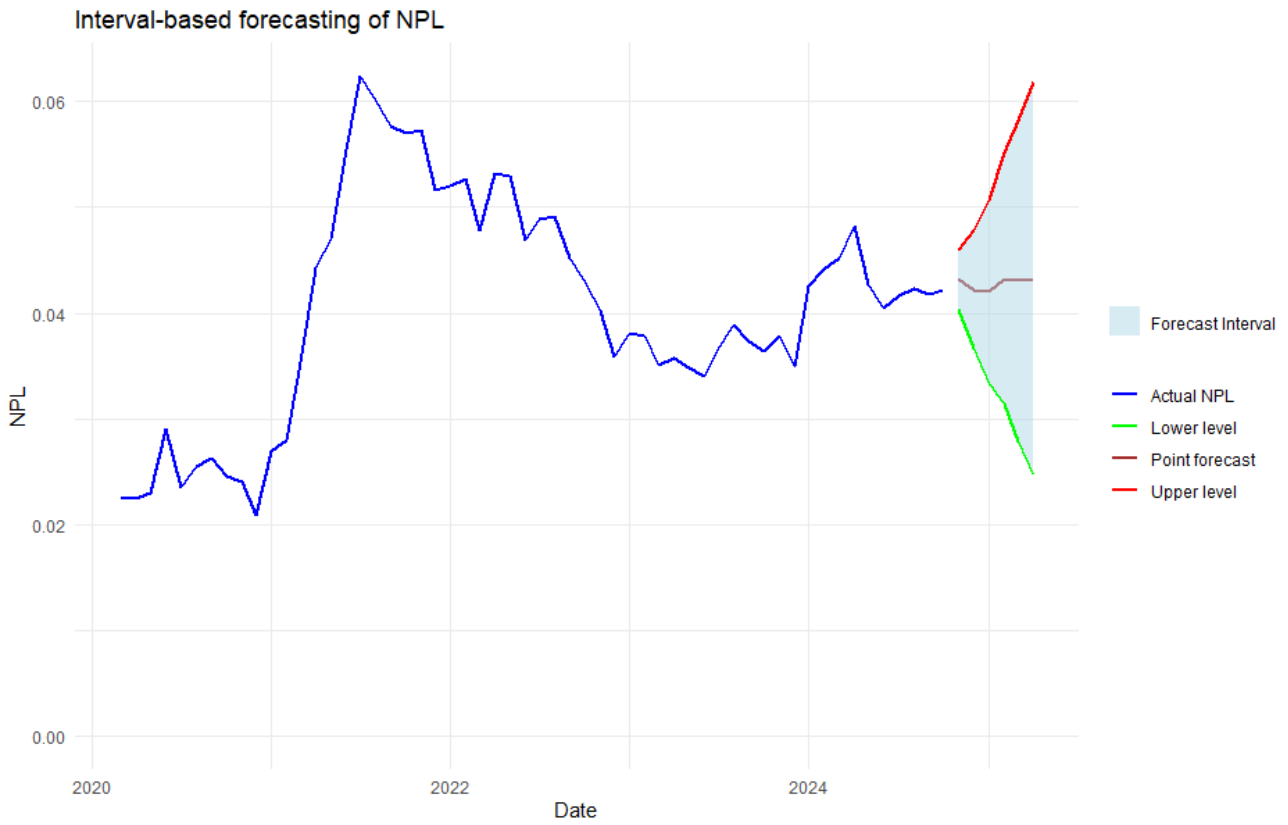
Note: *p<0.1; **p<0.05; ***p<0.01

associated with NPL rate. The positive coefficients for the second lag of GDP growth and loan interest rate in my VAR model, both around 0.196-0.197, indicate that these two variables have a delayed but significant effect on the NPL rate. A positive coefficient for the second lag of GDP growth (0.1962) suggests that an increase in GDP growth today may correlate with a rise in the NPL rate two periods (months) later. This might seem counterintuitive at first, as higher GDP growth often implies stronger economic conditions, which typically would lower loan default rates. Possible explanation for positive association between GDP growth and NPL is that high growth could encourage borrowers to take on more credit, which temporarily maintains low NPL rates. But as these debts mature, some borrowers may face difficulties in repayment, resulting in higher NPL rates after a couple of periods. The positive coefficient of interest rate aligns with economic expectations, as a higher interest rate increases the cost of borrowing. Over time, this can strain borrowers, particularly those with variable-rate loans, as their interest obligations rise. The delayed response in NPL could indicate that it takes some time for borrowers to start facing significant repayment challenges, which are then reflected in higher defaults after two months.

After creating a VAR model, I forecasted the NPL rate for the next six months using the variables included in the model (See Picture 2). Before proceeding with the future forecast, I tested the model on the existing period, and the results showed that the forecasted NPL rate was very close to the actual values, especially for the first month, indicating the model's reliability.

For the forward-looking forecast, I included a 60% prediction interval to estimate 20th and 80th percentile prediction values. This approach provides a range of possible outcomes, allowing for the analysis of different economic scenarios and the associated risk levels for NPL, thus offering valuable insights for planning under varying economic conditions.

According to the point estimation, NPL rate in commercial banks is forecasted to be around 4.2% - 4.3% for the next 6 months and lower prediction level is calculated as 4% for the next month and can reach down until 2.5% at the end of 6 months. Similarly, upper prediction level is estimated to be around 4.6% for the first month and expected to go as high as 6.2% at the end of 6 months.



Picture 2. Interval-based forecasting of NPL for the next 6 months.

Conclusion

The positive growing trend of the share of non-performing loans in the credit portfolio at lending institutions of Uzbekistan is of a concern to the financial professionals and policymakers. In order to mitigate this risk, they have to take proactive measures. One of the important aspects in tackling this issue is the implementation of a robust credit risk management system that ensures the stability and health of the lending sector.

The developed economies have been widely adopting the Basel standards. These standards provide a wide range of frameworks to mitigate the risk. Integrating them into our credit risk management practices would enhance the resilience and credibility of our financial system. Some of the BASEL regulatory frameworks that are relevant in credit risk management are risk-based capital requirements, calculation of risk-weighted assets (RWA) and set standards for financial ratios. By adopting BASEL standards, our financial institutions can improve in managing credit risk, transform into more transparent organizations, and ensure a more stable and secure banking environment. This adoption will not only strengthen our domestic financial system but also foster greater confidence among international investors and stakeholders.

In summary, implementing these recommendations, including integrating advanced credit modeling techniques and establishing a robust data warehouse, aligns with and supports the goals of the "Digital Economy - 2030" initiative outlined in presidential decree PF-6079

dated October 5, 2020. By enhancing credit risk management through advanced analytics and improving data infrastructure, lending institutions can contribute to the broader objective of advancing digital transformation in the financial sector. These measures will drive innovation, operational efficiency, and data-driven decision-making, thereby accelerating progress toward a more resilient and technologically advanced economy.

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