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Technical Development of Countercyclical Capital Buffer Implementation in Mongolia's Banking Sector

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Abstract

This paper attempts to develop a framework for implementing the Countercyclical Capital Buffer (CCyB) in Mongolia's banking sector by identifying early warning indicators of systemic risk and examining the impact of capital adequacy on bank lending. Using quarterly data from 2000 to 2024, the study employs signaling (area under the receiver operating characteristic curve), logit regression, decision tree analysis, and panel regression techniques. Results show that credit-to-GDP gaps, external and fiscal imbalances are strong predictors of banking crises. Additionally, a one-percentage-point increase in the capital adequacy ratio reduces loan-to-asset ratio by 0.74 percentage points, with the effect more pronounced among larger banks. These findings support the case for a tailored, data-driven CCyB framework in Mongolia and offer broader implications for countercyclical policy design in small, open and commodity-dependent economies.

Keywords: countercyclical capital buffer (CCyB), capital adequacy ratio, bank lending, early warning indicators, financial stability

JEL: E58, G28, G32, C23

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The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the BANK OF MONGOLIA.

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INTRODUCTION

If the global-wide financial crisis were to reoccur, financial institutions would likely be more resilient than during previous episodes, due in part to the implementation of macroprudential policy instruments such as the countercyclical capital buffer (CCyB). The CCyB plays a critical role in curbing excessive credit growth during financial upswings and ensuring that sufficient capital reserves are available to absorb losses during downturns. Its effectiveness was notably demonstrated during the economic disruptions caused by the COVID-19 pandemic (Dursun-de Neef, Schandlbauer, & Wittig, 2023). Importantly, the CCyB not only serves to restrain overheating in the financial sector but also facilitates recovery by allowing capital to be released when economic conditions deteriorate, thus helping to stabilize credit supply and support real economic activity.

The successful deployment of the CCyB requires deliberate calibration at each stage of its design and implementation. This entails setting capital buffer requirements tailored to individual institutions to safeguard the continuous functioning of the banking system, while also ensuring that sufficient capital is accumulated during expansionary periods and released strategically during recessions. Thus, the timing and sequencing of CCyB implementation are therefore central to its effectiveness as a countercyclical instrument.

A growing body of theoretical and empirical research emphasizes the importance of a structured, evidence-based approach in CCyB calibration. While aligning with global regulatory trends is valuable, the implementation of CCyBs must be tailored to country-specific macro-financial conditions. In bank-dominated economies with shallow capital markets, and high exposure to external shocks – such as Mongolia – macroeconomic volatility can intensify credit cycles. Adopting international frameworks without adaptation may therefore prove ineffective or even counterproductive.

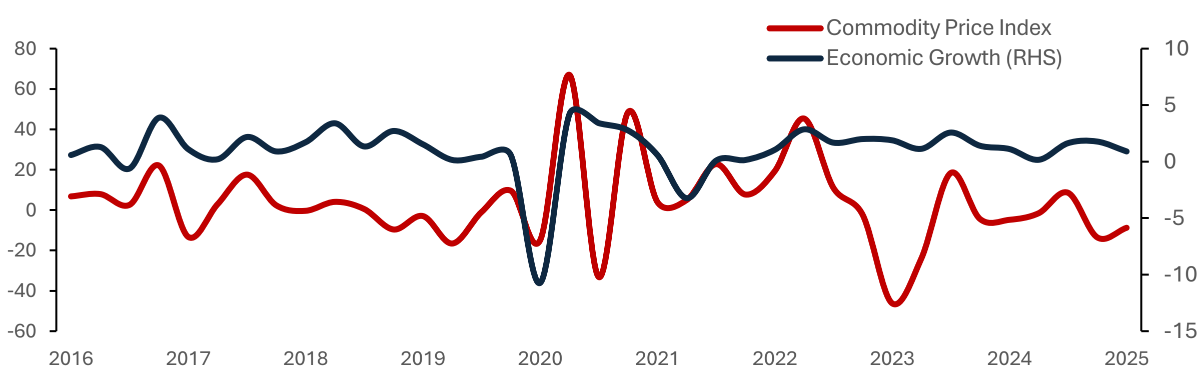
Mongolia' unique geopolitical position, its high reliance on commodity exports, and the concentrated structure of its financial system complicate the direct adoption of global regulatory models. These structural characteristics necessitate context-specific adjustments and informed judgment in localizing macroprudential tools. Accordingly, the development of CCyB framework for Mongolia must be grounded in empirical analysis that captures the structural and cyclical dynamics of the domestic economy. This study aims to contribute to the effort by proposing an evidence-based approach to CCyB implementation in Mongolia – drawing on international best practices while adapting them to the country's institutional and economic realities.

The remainder of this paper is structured as follows: Section 2 provides contextual background on Mongolia's banking sector, including its macro-financial environment and the rationale for CCyB. Section 3 presents a review of relevant literature, covering both early warning indicator models and empirical studies employing panel regression analysis. Section 4 describes the dataset and variables used in the analysis, and their relevance to the research objectives. Section 5 details the methodological approach, which includes the signaling method, discrete choice models, decision-tree classification, and panel regression techniques. Section 6 reports the empirical results from each method, while Section 7 summarizes the main findings and discusses policy implications. Section 8 lists references, and Section 9 provides supplementary materials and appendices used in the analysis.

BACKGROUND INFORMATION

Mongolia– a developing, landlocked nation in Central Asia situated between China and Russia – has an economy which is heavily reliant on commodity markets and remains highly vulnerable to external shocks **(Figure 1)**. Historically, in response to periods of strong capital inflows and favorable external conditions, Mongolia has tended to pursue procyclical macroeconomic policies, including expansionary fiscal spending and accommodative monetary measures. Such policy choices have often exacerbated macroeconomic imbalances, contributing to overheating of the economy and increasing the likelihood of financial instability (Byambasuren & Khasar, 2018). Considering these recurring challenges, it is essential for the policymakers to shift toward a more countercyclical policy framework. This would involve timely implementation of macroprudential, and fiscal tools aimed at moderating economic volatility, reducing systemic risks, and supporting sustainable, long-term economic growth.

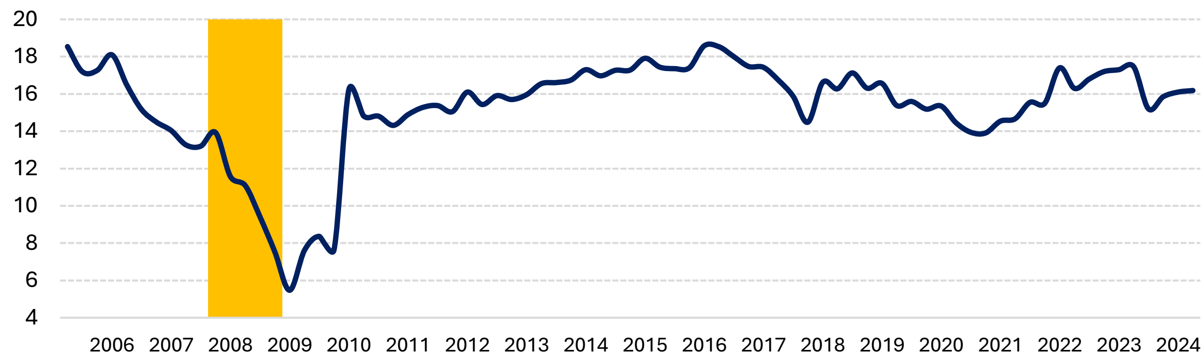
Figure 1: Economic Growth and Commodity Price Index Fluctuation (2016Q1-2025Q1)



According to the Law of Mongolia on Central Bank, the Central Bank (hereafter the Bank of Mongolia, BoM)'s primary objective is to "promote balanced and sustainable development of the national economy, through maintaining the stability of money, financial markets and the banking system" (Government of Mongolia, 1996). Furthermore, through the legal amendments made in 2018 the BoM gained the authority to enact macroprudential policy and has employed various tools to limit financial systemic risks. This statutory revision was made in accordance with bank dominance in Mongolia's financial sector, taking up to 90% of the total assets. Accordingly, implementing regulatory measures for banks is a necessary approach to safeguarding the stability of the financial system.

To pursue the objective of ensuring financial stability, BoM has extensive powers to introduce early intervention measures and financial restructuring of banks; on top of its full authority to demand banks to hold additional capital above the regulatory minimum, to require them to use net profits to strenghten their own funds.

Figure 2:Quarterly Capital Adequacy Ratio of the Mongolian Banking System (2006Q1-2025Q1) with highlighted Banking Crisis Period (2008Q3-2009Q3)



Capital adequacy is legally defined under Article 3.1.9 of the Law on Banking as "the assessment of the adequacy of the bank's capital base to cover losses caused by financial and operational risks". The primary quantitative indicator used to assess this is the Capital Adequacy Ratio (CAR), which is calculated as the ratio of regulatory capital to risk-weighted assets. According to the "*Regulations on Setting and Monitoring Prudential Ratios*", the minimum CAR requirement is currently set at 12 percent. Historically, CAR levels in Mongolia's banking sector have fluctuated in response to macroeconomic cycles, regulatory reforms and crisis events **(Figure 2)**. The most notable decline in capital adequacy occurred during the 2008-2009 banking crisis, coinciding with severe stress in the financial system. This episode, characterized by the collapse of two banks and the introduction of emergency legislative measures, aligns with the crisis period identified in the dataset of Laeven and Valencia (2020).

LITERATURE REVIEW

There are two main sources of guidance for the development of the CCyB. The most renowned guidance utilized by majority of the policymakers, to introduce the CCyB as a macroprudential tool, is Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems (Basel Committee on Banking Supervision, 2011). For effective and comprehensive implementation of this tool, policy implementing jurisdictions are expected to monitor systemic risk using forward-looking indicators, such as credit gaps and financial imbalances. In its subsequent guidance on the implementation of CCyB, the credit-to-GDP gap[1] is highlighted as the principal indicator for evaluating excessive credit growth and informing buffer rate decisions. Following this, in 2014, the European Systemic Risk Board (ESRB) published additional guidance on setting the CCyB rate. This document provides a more comprehensive analytical framework for identifying effective early warning indicators. The ESRB classifies potential indicators into five categories: real-economy variables, credit-related variables, market-based variables, property-related variables, and bank balance sheet variables. Among these, the credit-to-GDP gap consistently demonstrates the strongest performance in predicting financial crises and is widely regarded as the most reliable indicator for this purpose.

Beyond the above-mentioned technical guidance documents, numerous researchers have contributed to the development and effective calibration of CCyB implementation through a diverse range of methodologies. Based on the scope of their analysis, this body of literature can broadly be divided into two distinct approaches, early warning model and panel regression. As mentioned above, certain macro-financial indicators serve as early warning signals prior to financial crises. However, due to the limited number of crises data and the restricted analysis of robustness tests, researchers conducted an alternative method to identify relevant early warning indicators. Consecutively, further take on this approach focuses on literature that uses panel datasets to analyze early warning indicators across different countries. Then, the second approach is panel regression methodology which examines the changes in the level of lending in response to adjustments in financial institutions' capital adequacy. Adoption of the panel regression approach offers robust empirical evidence due to its consideration of fixed effects while accounting for heterogeneity.

EARLY WARNING MODEL APPROACHES

The first category focuses on country-specific case studies, where researchers analyze the implementation and effectiveness of early warning indicators using data from a single national context. Alessandri, Bologna, Fiori, and Sette (2015) investigate the implementation of the CCyB framework in Italy. The study highlights the effectiveness of the two-sided Hodrick-Prescott (HP) filter in estimating the credit-to-GDP gap and uses regression analysis to assess the predictive performance of various macro-financial indicators. Among the variables analyzed, credit-related indicators, output growth,

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[1] The deviation of the ratio of total credit to the private non-financial sector to GDP from its long-term trend.

$$Credit - to - GDP\ Gap_t = \left(\frac{Credit_t}{GDP_t}\right) - \left(\frac{Credit}{GDP}\right)_t^{trend}$$

unemployment rates, and real estate price gaps demonstrate significant predictive power for financial system stress, expressed in terms of non-performing loans. Castro, Estrada, and Martínez (2016) define three major stress events in the Spanish banking system since the 1960s to identify effective early warning indicators of financial vulnerabilities. Employing the Area Under the Receiver Operating Characteristic (AUROC) curve as the main evaluation method, the study finds that indicators such as credit intensity, private debt sustainability, real estate prices, and external imbalances—alongside the credit-to-GDP gap—are useful in predicting financial crises. Conversely, Galán (2019) further evaluates the role of filtering methods in measuring credit gaps using Spanish data. The study compares the performance of the HP filter with alternative techniques such as Butterworth, Christiano-Fitzgerald, and model-based filters. Results indicate that credit-to-GDP gap estimated using the HP filter demonstrates superior predictive performance for financial crises, particularly when less restrictive assumptions regarding the length of financial cycles are applied (Galán, 2019).

To examine the shortcomings of the widely used credit-to-GDP gap, Jokipii, Monnin, and Temperton (2021) conduct a study that highlights two key limitations associated with the indicator. First, changes in nominal GDP—rather than credit volumes—can distort the gap, potentially misrepresenting risk accumulation. Second, the HP filter itself introduces measurement issues. Despite these concerns, the study concludes that the BIS gap remains a useful indicator for excess credit in Switzerland. More recently, Škrinjarić (2022) applies regime-switching models to forecast financial distress in Croatia. The findings align with earlier research conclusions, confirming the relevance of the credit-to-GDP gap and growth rates of credit. Additionally, other indicators such as house price and rent dynamics, construction activity, external imbalances, bank balance sheet metrics, interest rate margins, and stock market-based measures are also identified as potential predictors of systemic financial stress.

Financial crises are system-wide and rare events, serving as obstacles for researchers to draw concrete conclusions and/or test for robustness of the findings. Thus, it is common to combine data from multiple sources to assess the valid performance of early warning indicators. Drehmann, Borio, and Tsatsaronis (2011) conduct empirical research using a wide range of data from 36 countries spanning from 1960 to 2010. Their findings reveal that the credit-to-GDP gap is the most reliable leading indicator for forecasting financial crises, while credit spreads are useful in identifying the release phase of crises. This study highlights the critical role of credit-based indicators in assessing financial vulnerabilities. Similarly, Behn, Gambacorta, and Mistrulli (2013) examine macro-financial variables for predicting financial distress, using data between 1982 and 2012 from 23 European countries. Their findings suggest that, aside from credit-related variables, equity and house prices are reliable predictors of financial crises. Geršl and Seidler (2015) run simulations on data between 1990 and 2014 from 16 Central, Eastern, and Southeastern European countries. This study critically examines the limitations and sensitivities of utilizing the HP filter – especially in emerging economies with short or volatile credit data. The researchers conclude that credit-to-GDP gap is a useful indicator for guiding the setting of CCyB in the Central, Eastern, and Southeastern European countries, but they also caution against overreliance on this indicator – particularly in less mature financial systems (Geršl & Seidler, 2015). Then Simo K., Dias, and Figueira (2018) extend the previous research by testing around 50 macro-financial indicators for their ability to serve as early-warning signals for domestic systemic financial crises across Eurozone countries and the UK. They utilize a dataset spanning from 1970 to 2016 and test a variety of transformations, including growth rates and HP-filtered gaps. Consequently, the analysis identifies the credit-to-GDP gap, household credit-to-GDP ratio, housing price-to-income ratio, the current account-to-GDP ratio, high-yield spread, and the VIX index as the most informative indicators for predicting financial crises – findings that align closely with earlier empirical research.

Further research by Tolo, Drehmann, Juselius, and Østbye (2018) examine the performance of leading indicators from six categories identified by the ESRB using EU countries' data. Their study emphasizes the predictive power of the credit-to-GDP gap, debt-service ratios, and real estate price valuation measures as key early-warning indicators. In addition, market-based indicators such as the VIX index, stock market volatility, international credit spreads, and various banking sector ratios are identified as significant contributors to early detection of financial distress, aligning with insights from the ESRB (2014). Lang and Welz (2018) compare the Basel credit gap with theory-based credit gaps using data from 12 European countries since the 1980s. They argue that theory-based credit gaps offer advantages, including clearer economic interpretations and avoiding large negative values following financial crises. The study suggests that such gaps could serve as a valuable complement to the HP filter method, particularly in refining the accuracy of early warning signals. Lastly, Baba et al. (2020) noted a limitation of the Basel credit gap, observing that after a significant credit boom, the Basel gap often remains negative, incorrectly suggesting that credit should return to its peak levels. To overcome this, the authors propose two alternative methods - model-based multivariate filtering and a fundamental-based equilibrium correction (EC) model - to assess the credit-to-GDP gap. Their research indicates that these methods could provide valuable insights and complement traditional approaches, offering a more comprehensive view for policymakers.

PANEL REGRESSION

A foundational body of empirical research consistently finds that bank capital buffers are inherently cyclical, tending to increase during economic expansions and decline during contractions, which poses challenges for financial stability (Jokipii & Milne, 2008). This cyclicality implies that in downturns, when credit is most needed, banks tend to reduce their capacity to lend, exacerbating economic contractions (Tabak, Noronha, & Cajueiro, 2011). Jokipii and Milne (2008), analyzing EU-15[2] banks, and Tabak et al. (2011), using Brazilian panel data, highlight this pattern and conclude that such procyclical behavior justifies macroprudential countermeasures such as the CCyB.

Understanding what drives banks to accumulate or deplete capital buffers is critical for designing effective CCyB mechanisms. Fonseca and González (2010) show that cross-country variations in buffer behavior can be explained by differences in regulatory intensity, market competition, and the cost of capital. Banks operating in less competitive environments or under looser regulatory regimes tend to hold smaller buffers, raising questions about how incentives are structured. Similarly, Shim (2013) explores this concept further in the context of Chinese commercial banks. His findings suggest that banks with diversified income sources and strong internal risk management systems are better positioned to smooth capital buffer adjustments over the cycle. This is particularly relevant for Mongolia, where commercial banks are relatively undiversified and reliant on interest income, increasing their vulnerability to procyclical lending behavior. Jokipii and Milne (2008) also emphasize institutional variation, noting that capital buffer behavior is more predictable in countries with well-defined prudential frameworks.

The effectiveness of CCyBs during crises has become more empirically testable in recent years. Dursun-de Neef, Schandlbauer, and Wittig (2023) provide a compelling case study using balance sheet loan data during the COVID-19 crisis. Their panel regression analysis shows that countries that released CCyBs promptly experienced relatively stronger credit supply, confirming the stabilizing role of the tool during economic downturns. Auer, Bogdanova, and Levina (2022) extend this by showing that CCyBs influence not just the volume but also the composition of bank lending, steering it away from riskier segments. Behncke (2022) complements this with panel evidence that macroprudential measures – including CCyBs – help reduce credit risk and enhance bank resilience during downturns. Older empirical work also confirms that capital requirements influence lending behavior. Bridges, Gregory, Nielsen, and Pezzini (2015), using granular UK data, show that increases in capital requirements lead to a significant contraction in credit growth. Similarly, Carlon, Schaeck, and Čihák (2013) employ a matched bank methodology to demonstrate how capital ratios influence bank lending during stressed periods; Jonghe, Vander Vennet, and Wuyts (2019) provide additional support by examining the impact of Pillar 2 requirements,

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[2] The fifteen member states (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom) of the European Union prior to the major enlargement in 2014

concluding that capital policy changes directly shape credit supply decisions at the bank level.

To operationalize CCyBs effectively, model-based approaches and calibration tools are key. Behn et al. (2013) employ early-warning models and argue that credit-to-GDP gap, despite its limitations, remains a useful anchor for timing buffer adjustments. They advocate for indicator-based frameworks complemented by supervisory judgment. Similarly, Coffinet, Gambacorta, and Ülkü (2013) stress the need for forward-looking tools like composite risk indices and scenario analysis, especially for economies with volatile macro-financial dynamics such as Mongolia. In parallel, macroprudential readiness in emerging markets remains as a central concern. Guidara, Soumaré, and Tchana (2013) and Kumar & Meena (2022) both point to the importance of institutional strength, supervisory consistency and policy communication. Fonseca and González (2010) emphasize that regulatory credibility fundamentally shapes banks' buffer decisions, reinforcing the need for clear macroprudential mandates and gradual implementation strategies in developing jurisdictions.

In sum, the reviewed literature offers robust empirical support for CCyBs as a means of smoothing credit cycles and building systemic resilience. Key factors for success include timing guided by both indicators and judgment, the use of forward-looking models, institutional readiness and supervisory capacity, and clear communication strategies. These findings provide a foundation for Mongolia's technical roadmap toward developing and operationalizing a CCyB framework tailored to its evolving banking system.

DATA

4.1. Data related to early warning indicators

A key step in operationalizing the CCyB is the development of early warning models, which require the identification of past episodes of banking sector distress. As defined by Laeven and Valencia (2020) a single episode of systemic banking crisis in Mongolia, which occurred between 2008Q3 and 2009Q3. During this period, the banking sector experienced acute stress, resulting in the failure of two banks and prompting the enactment of the Law on Guarantee of Bank Deposits.

This research aims to include all relevant indicators that may significantly contribute to predicting the above-mentioned crisis, drawing from the categories outlined in ESRB's guidance[3]. The dataset spans the period from 2000Q1 to 2024Q4 and must encompass banking crisis episodes.

[3] *Recommendation of the ESRB on guidance for setting countercyclical buffer rates, 2014*

Three primary criteria are employed in the selection of variables:

(i) each indicator must have a strong economic rationale for predicting banking crises, either theoretically or supported by existing literature;

(ii) the data must be available consistently throughout the estimation period; and

(iii) the indicator must be reported at a quarterly frequency.

In accordance with the criteria for predicting banking crises, the selected variables may be classified under the following categories of economic rationale.

4.1.1. Measures of credit developments

Although credit is an important factor for financial deepening and economic development, its excessive growth has a negative effect on long-term stable economic growth, typically entailing substantial costs (Bakker, Dell'Ariccia, Laeven, Vandenbussche, Igan, & Tong, 2012). Thus, since the Global Financial Crisis, many countries have increasingly focused on monitoring credit growth. The BIS issued a guidance on implementing "Countercyclical capital buffer", which emphasized credit-to-GDP gap as the main indicator to predict banking distress. In addition to this, a growing body of empirical research – such as Kalatie, Laakkonen, and Tölö (2015) – has found credit-related indicators to be statistically significant predictors of financial crises. In the case of Mongolia, the economy is heavily dependent on the commodity market, and banks tend to ease credit requirements and increase lending during periods of positive external shocks (Doojav & Luvsannyam, 2017). Such procyclical behavior contributes to excessive credit growth and heightens systemic vulnerability.

From this category, we have selected the **credit to GDP gap, credit to non-mining GDP gap and credit growth** as potential early warning indicators.

To enhance the performance of credit-related indicators, we constructed several versions of the credit-to-GDP gap using nominal credit, real credit, and adjusted credit measures. The adjusted credit series excludes lending associated with quasi-fiscal operations, to isolate core bank-based intermediation and better reflect genuine lending behavior. We also utilize both total GDP and non-mining GDP as denominator measures to account for the structure of Mongolia's economy. Non-mining GDP provides a more stable economic indicator by excluding the highly volatile mining sector, thereby reducing noise in the estimated credit gaps.

4.1.2. Measures of private sector debt burden

These indicators measure the level of borrowers' indebtedness. If households and firms carry debt obligations that exceed their repayment capacity, it indicates an unsustainable level of leverage, thereby increasing the likelihood of defaults on debt servicing. Consequently, banks are directly exposed to elevated credit risk stemming from excessive private sector debt, while the broader economy may suffer adverse effects due to a decline in consumption and investment. Debt-to-income ratio and debt service are commonly used indicators within this category (Kalatie et al., 2015). According to the European Systemic Risk Board's (2014) recommendation, debt to service ratios of non-financial corporations may be a less effective predictor of financial crisis compared to household debt burdens. Furthermore, in economies with less developed financial sectors, reliable data related to this category is often limited or unavailable.

Considering this, we have chosen **household debt-to-GDP ratio, debt service ratio and household debt growth** as proxy indicators of household indebtedness. Due to the unavailability of actual household debt service data, we estimate the debt service ratio by multiplying the interest rate on newly issued loans with the individual loan amount.

4.1.3. Measures of potential overvaluation of property prices

Following the credit development indicators, variables related to real estate sector can make potential predictors of banking crisis. Borio and Drehmann (2009) argue that the combination of rapid credit growth and rising real estate prices poses significant risks to financial stability. This is largely because residential property purchases are predominantly financed through bank lending, and the property prices tend to increase rapidly during periods of economic expansion as banks tend to lower credit requirements. Such conditions increase banks' exposure to the real estate market, since collateral values become inflated during the boom period. When property prices subsequently decline, the overvaluation of collateral can result in substantial losses for banks. This dynamic was notably observed during the Global Financial Crisis. However, due to data limitations, it is not feasible to empirically test indicators in this category within the current analysis.

4.1.4. Measures of external imbalances

As a small and open economy, Mongolia is highly reliant on global economic conditions and the commodity market. Consequently, external imbalances may serve as key indicators of potential vulnerabilities within the financial system. Several academics have identified the current account deficit as a relevant predictor of banking crisis, but this link tends to be weaker in emerging markets (Kalatie et al., 2015). The rationale is that when domestic savings are not sufficient for credit expansion, foreign capital inflows may compensate for the shortfall, contributing to current account deficits and facilitating excessive credit growth – an environment conducive to financial instability. Nevertheless, in the context of Mongolia this concept may not fully apply. Given the limited integration of the Mongolian financial system with international markets, most of the credit demand is met by domestic financial institutions. In Mongolia's case, a current account surplus may instead indicate excess domestic savings, which can fuel increased lending activity and, in turn, contribute to unsustainable credit growth.

Thus, we have selected **"Current account-to-GDP ratio", "Capital account-to-GDP ratio", "Balance of payments-to-GDP ratio", "Year-on-year growth of export prices"** as potential early warning indicators.

4.1.5. Measures of potential mispricing of risk

These indicators are widely utilized in advanced economies and are less common in developing countries where financial systems remain underdeveloped. According to Kalatie et al. (2015), variations in banks' interest rate margins and changes in stock prices or risk premiums on securities may serve as effective early warning indicators. For instance, in times of positive economic development, banks tend to reduce the spread between interest rates on low-risk assets and lending rates, reflecting diminished risk perceptions. Similar patterns can be observed in securities markets, where declining risk premiums are indicative of heightened investor confidence. Such behaviors tend to stimulate credit expansion and contribute to overheating in the financial sector, thereby increasing systemic risk. However, the sustained decline in Mongolia's loan market risk premium between 2000 and 2012 suggests that this indicator may not be appropriate for analyzing or predicting the 2008 banking crisis.

Given the underdevelopment of the country's capital markets and limitations in data availability, the **year-on-year growth of the Top 20 Index—**which tracks the performance of the top 20 companies listed on the Mongolian Stock Exchange—has been selected as a potential early warning indicator.

4.1.6. Measures of the strength of the bank balance sheet

Bank balance sheet items – particularly indicators related to asset quality, liquidity, solvency and profitability – could be possible early warning indicators of banking crisis (ESRB, 2014). When banks are unable to meet loan demand through core liabilities, such as deposits, they often resort to increasing their reliance on market-based funding sources, or non-core liabilities. This shift raises the vulnerability of the banking system, as non-core liabilities are more prone to sudden withdrawals during economic downturns, thereby heightening liquidity risk. Kinda, Plane, and Vasishtha (2016) note that in response to positive external shocks, domestic bank deposits may increase, but these inflows are often reversed significantly during periods of negative shocks – a dynamic that is particularly pronounced in countries characterized by high public debt, underdeveloped financial markets, and weak institutional frameworks. Within this category, we have selected "**Equity multiplier", "Leverage" and "Loan to deposit ratio"** as potential early warning indicators.

In addition, we have identified **"M2", the "budget balance-to-GDP ratio", and the "budget expenditure-to-GDP ratio"** as supplementary indicators tailored to the specific structural features of Mongolia's economy and financial system. For instance, during periods of high capital inflow, the government often adopts expansionary fiscal policies, which can stimulate bank lending and contribute to the accumulation of systemic financial risk.

4.2. Data for panel regression analysis

The dataset used for the panel regression analysis is compiled from the supervisory financial statements submitted quarterly by commercial banks to the BoM. The dataset spans the period from 2008Q1 to 2024Q4. It includes quarterly observations for 8 licensed commercial banks operating in Mongolia. To maintain the panel data balance and to retain sufficient coverage for reliable empirical analysis, this research exclusively includes data from fully operating banks.

All data used in the regressions are aggregated and processed internally, where necessary, and are verified against publicly disclosed financial statements and official central bank publications. The unit of observation is the bank-quarter. That is, each row in the dataset represents one bank's financial performance for one quarter. Given the quarterly frequency and a time horizon of 68 quarters (17 years), the panel allows for the investigation of both cross-sectional and temporal variation in bank behavior, especially in response to changes in capital adequacy and broader macro-financial conditions.

Table 1: Variables used in panel regression

Variable	***Description***	***Transformation/Notes***
Loans	Loans / Total Assets	Dependent variable
CAR	Capital Adequacy Ratio[4]	Lagged
Capital	Total Capital / Total Assets	Lagged
Provision	Loan Loss Provisions / Total Assets	Lagged
Net Interest Income	Net Interest Income / Total Assets	Lagged
Profit	Net Profit / Total Assets	Lagged
Cash	Cash Holdings / Total Assets	Lagged
Deposits	Deposits / Total Assets	Lagged
Log (Assets)	Logarithm of Total Assets	Lagged

[4] Basel definition

The dependent variable in the regression models is the loan-to-asset ratio, which measures the proportion of a bank's resources allocated to lending. This ratio standardizes credit supply across banks of varying sizes and is commonly used as a proxy for bank lending behavior. The key explanatory variable is the lagged Capital Adequacy Ratio (CAR), which reflects the regulatory capital buffer maintained by each bank. Additional control variables include a set of balance sheet and income indicators, all lagged by one period and expressed as ratios of total assets. Logarithm of total assets is included as a proxy for bank size. Table 1 summarizes the variables used in the panel regression analysis.

All financial variables are normalized by total assets to ensure comparability across institutions of different sizes and to minimize the impact of scale effects. The use of lagged values also mitigates concerns of reverse causality.

METHODOLOGY

5.1. Early Warning Models (EWMs)

According to the ESRB (2014), three main approaches are commonly used to identify potential early warning indicators of banking crisis: the signaling approach, the discrete choice model, and decision tree learning.

5.1.1. Signaling approach

The signaling approach is the most widely adopted method in the early warning literature. Initially developed by Kaminsky and Reinhart (1999), it has been enhanced through contributions from numerous researchers. The core concept of this approach is that a signal is issued when the value of a selected variable exceeds a pre-determined threshold. In most empirical applications, the signaling approach is implemented using a univariate approach, where each indicator is assessed independently. However, some studies have explored multivariate adaptations – incorporating a combination of variables – and have reported improved predictive performance. Notably, this approach performs better for country-specific EWMs (Davis & Karim, 2008).

The approach organizes outcomes into a confusion matrix, which classifies observations based on whether a signal was issued and whether a crisis occurred within a designated forecast horizon. A signal followed by a crisis within the specified forecast horizon is labeled as a true positive (A), while a signal without a subsequent crisis is considered a false positive (B). If no signal is given but a crisis does occur, it is categorized as a false negative (C). Lastly, if neither a signal is issued nor a crisis occurs, it is regarded as a true negative (D). These classifications are illustrated in Table 1.

Table *2*: Confusion matrix

	Crisis	No Crisis
Signal	A (True Positive)	B (False Positive)
No Signal	C (False Negative)	D (True Negative)

From this matrix, several key performance metrics are derived:

$$\textbf{Signal ratio} \text{ (True positive rate)} = \frac{A}{A+C}$$

$$\textbf{Noise ratio} \text{ (False positive rate or Type II error)} = \frac{B}{B+D}$$

$$\textbf{Type I error rate (1- true positive rate)} = \frac{C}{A+C}$$

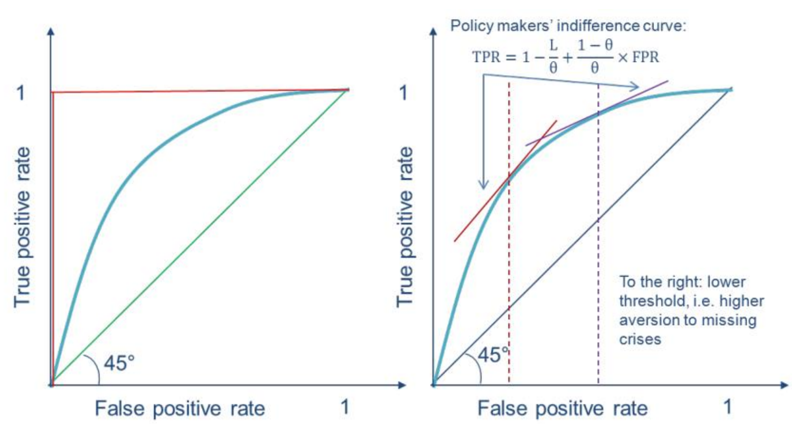
$$\textbf{Policymakers' loss function:} \quad L = \theta\frac{C}{A+C} + (1 - \theta)\frac{B}{B+D}$$

where θ reprepsents the relative weight placed on missing a crisis (Type I error) compared to issuing a false alarm (Type II error).

The area under the receiver operating characteristic (AUROC) curve

To assess the overall predictive power of an indicator, the Receiver Operating Characteristics (ROC) curve is employed. The ROC curve illustrates the relationship between the false positive rate (noise) and the true positive rate (signal) across all possible threshold values. High thresholds are positioned near the origin, meaning that fewer signals are generated, which leads to fewer correctly identified crises and fewer false positives. On the other hand, low thresholds are closer to the (1,1) point, where more signals are issued, resulting in more correct crisis identifications but also an increase in false signals.

Figure 3: The ROC and AUROC



Source: ESRB (2014)

The AUROC is calculated as the area under the ROC curve and serves as a summary statistic that ranges from 0 to 1. An AUROC value of 0.5 suggests that the indicator is uninformative (as illustrated by the 45° green line in the left panel of **Figure 3**). An AUROC greater than 0.5 indicates that the selected variable is informative and typically exhibits higher values before crises occur, shown as the blue curve in the left panel of **Figure 3**. An AUROC of 1 represents a perfect indicator, illustrated by the red line in the left panel of **Figure 3**.

5.1.2. Discrete choice

Next method in EWM development is the discrete choice approach. Frankel and Rose (1996), Hardy and Pararbasioglu (1998) and Demirgüç-Kunt and Detragiache (1999) are the founders of this method. In a discrete choice model, binary classification is used to link a set of explanatory variables to the likelihood of a systemic banking crisis. This is done using either a probit or logit function, which transforms the variables into a continuous probability score between 0 and 1, indicating the likelihood of a crisis. When the probability goes beyond a set threshold, it activates a signal. Unlike the basic signaling approach, discrete choice models can accommodate multiple indicators simultaneously, allowing for more complex relationships between variables.

5.1.3. Decision tree

The third EWM method, as proposed by Alessi and Detken (2014), is decision tree learning. A decision tree is a supervised machine learning algorithm that recursively partitions the data based on selected indicator thresholds to classify observations into either tranquil or pre-crisis periods. This approach identifies both the most relevant indicators and their corresponding threshold values for crisis prediction. The performance of a decision tree is highly sensitive to the choice of input variables. To enhance reliability and robustness, more advanced variants such as random forests can be employed. Random forests generate and aggregate predictions from numerous bootstrapped trees, improving the model's ability to identify the most influential indicators and reducing overfitting.

5.2. Panel regression

The panel regression model estimates the relationship between capital adequacy and bank lending measures by the loan-to-asset ratio, over the period between 2008 and 2024. The dependent variable is defined as the loan-to-asset ratio, capturing the available proportion of bank resources to be allocated to lending. This ratio serves as a standardized measure of credit supply across banks of varying sizes. The key independent variable is the lagged CAR, which reflects the regulatory capital buffer maintained by each bank. Additional explanatory variables include lagged financial performance and balance sheet indicators, all expressed as ratios of total assets to ensure comparability and to control for scale effects.

The inclusion of both bank and time fixed effects strengthens the causal interpretation by controlling for both structural and temporal heterogeneity. We employ fixed effects panel regression to control for unobservable, time-invariant heterogeneity across banks such as the governance structure, risk appetite, and fixed effects to capture common macroeconomic and policy shocks including but not limited to monetary easing, crisis periods and fiscal measures. The fixed effects of model specification helps isolate the within-bank variation over time, thereby strengthening the causal interpretation of the estimated coefficients.

The extent of bank lending is equated to the selected combination of lagged explanatory variables through the following structure:

$$\begin{aligned} Loans_{i,t} = \alpha &+ \beta_1 CAR_{i,t-1} + \beta_2 Capital_{i,t-1} + \beta_3 Provision_{i,t-1} \\ &+ \beta_4 Net\ Interest\ Income_{i,t-1} + \beta_5 Profit_{i,t-1} + \beta_6 Cash_{i,t-1} + \beta_7 Deposit_{i,t-1} \\ &+ \beta_8 \log(Assets_{i,t-1}) + \mu_i + \lambda_t + \epsilon_{i,t} \end{aligned}$$

where:

- $Loans_{i,t}$: Loan growth by bank i in period t
- $CAR_{i,t-1}$: Lagged Capital Adequacy Ratio
- $Capital_{i,t-1}$: Lagged total capital
- $Provision_{i,t-1}$: Lagged loan loss provision
- $Net\ Interest\ Income_{i,t-1}$: Lagged net interest income
- $Profit_{i,t-1}$: Lagged net profit
- $Cash_{i,t-1}$: Lagged cash holdings
- $Deposit_{i,t-1}$: Lagged deposits
- $\log(Assets_{i,t-1})$: Log of lagged total assets (proxy for bank size)
- μ_i: Bank fixed effects (included only in the “All banks” specification
- λ_t: Time fixed effects (included in all specifications)
- $\epsilon_{i,t}$: Error term

Selection of the explanatory variables are based on the CAMELS framework, which is a widely used supervisory tool for assessing the health of financial institutions, comprising of six components: Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk. The financial indicators used in the panel regression model – capital, provisions, net interest income, profit, cash, and deposits – can each be mapped to the relevant CAMELS components as follows:

Table *3*: CAMELS Classification and Rationale of Bank-Level Variables

Variable	CAMELS Component	Rationale
Capital	**C**apital adequacy	Reflects bank's ability to absorb losses, meet regulatory requirements, and maintain solvency under adverse conditions
Provision	**A**sset quality	Reflects the extent to which a bank anticipates and buffers against credit losses in its loan portfolio
Net Interest Income	**M**anagement quality	Reflects the effectiveness of interest risk management, asset-liability alignment, and strategic loan and deposit pricing
Profit	**E**arnings	Reflects bank's capacity to generate income from its asset base, absorb losses, and support capital accumulation
Cash	**L**iquidity	Measures bank's capacity to meet short-term obligations using highly liquid resources
Deposits	**S**ensitivity to market risk	Reflects bank's vulnerability to external market fluctuations and investor sentiment, serving as a transmission channel for macro-financial shocks

RESULTS

This section assesses all candidate early warning indicators by using the signaling approach (AUROC), the discrete choice approach (logit) and the decision tree approach outlined in Section 4, as well as panel regression analysis to evaluate the relationship between capital adequacy and bank lending dynamics.

6.1. Results of early warning models

6.1.1. AUROC and logit regression

Using both the signaling approach – based on the AUROC – and the discrete choice model, we evaluate the predictive performance and statistical significance of a ride range of candidate indicators.

Given the lack of a universally accepted methodology for calculating the credit gap, we apply both one-sided and two-sided HP filters using a range of smoothing parameters – including 25,000, 125,000, and 400,000 – to evaluate the sensitivity and predictive performance of different specifications. These variations aim to identify the most robust early warning indicators for anticipating banking sector vulnerabilities in the Mongolian context.

Table 4: Credit Development Results

Indicator	Transformation	Univariate AUROC	Logit coef
Credit to GDP ratio	nominal, HPF_1s gap with λ 25000	0.49	-1.09
	nominal_adj, HPF_1s gap with λ 25000	0.44	-0.51
	nominal, HPF_1s gap with λ 125000	0.65	7.68
	nominal_adj, HPF_1s gap with λ 125000	0.65	13.02
	nominal, HPF_1s gap with λ 400000	0.65	9.58
	nominal_adj, HPF_1s gap with λ 400000	0.72	15.34
	real, HPF_1s gap with λ 25000	0.77	17.47(**)
	real_adj, HPF_1s gap with λ 25000	0.76	17.08(*)
	real, HPF_1s gap with λ 125000	0.79	23.94(**)
	real_adj, HPF_1s gap with λ 125000	0.82	25.97(**)
	real, HPF_1s gap with λ 400000	0.83	25.43(**)
	real_adj, HPF_1s gap with λ 400000	0.83	28.96(***)
	nominal, HPF_2s gap with λ 25000	0.48	-1.54
	nominal_adj, HPF_2s gap with λ 25000	0.47	-0.47
	nominal, HPF_2s gap with λ 125000	0.52	0.5
	nominal_adj, HPF_2s gap with λ 125000	0.46	3.05
	nominal, HPF_2s gap with λ 400000	0.49	0.71
	nominal_adj, HPF_2s gap with λ 400000	0.46	2.36
	real, HPF_2s gap with λ 25000	0.61	3.12
	real_adj, HPF_2s gap with λ 25000	0.48	-0.95
	real, HPF_2s gap with λ 125000	0.62	2.99
	real_adj, HPF_2s gap with λ 125000	0.49	1.23
	real, HPF_2s gap with λ 400000	0.60	2.31
	real, HPF_2s gap with λ 400000	0.48	1.16
Total credit	1y growth	0.73	1.58
Total credit to non-mining GDP ratio	real, HPF_1s gap with λ 25000	0.79	15.41(**)
	real_adj, HPF_1s gap with λ 25000	0.68	11.58(*)
	real, HPF_1s gap with λ 125000	0.81	21.96(**)
	real_adj, HPF_1s gap with λ 125000	0.73	14.01(**)
	real, HPF_1s gap with λ 400000	0.83	23.66(**)
	real_adj, HPF_1s gap with λ 400000	0.75	14.11(**)
	real, HPF_2s gap with λ 25000	0.65	4.82
	real_adj, HPF_2s gap with λ 25000	0.59	7.28
	real, HPF_2s gap with λ 125000	0.61	3.56
	real_adj, HPF_2s gap with λ 125000	0.63	8.28
	real, HPF_2s gap with λ 400000	0.60	2.47
	Real_adj, HPF_2s gap with λ 400000	0.58	4.74

, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

The results indicate that the real credit-to-GDP gap indicators, particularly those computed using the one-sided HP filter, consistently outperform alternative specifications. For example, the real credit-to-non-mining GDP gap, filtered with the one-sided HP filter using a smoothing parameter of 400,000, achieves an AUROC score of 0.83, the highest among all indicators within the credit development category. Findings from the discrete choice model broadly align with those of the signaling approach, reinforcing the robustness of the results. Indicators with higher AUROC scores have also tended to exhibit statistically significant coefficients in the logit regression, further validating their predictive power.

Table 5: Private Sector Results

Indicator	Transformation	Univariate AUROC	Logit coef
HH credit to GDP ratio	nominal, HPF_1s gap with λ 25000	0.49	9.78
	nominal, HPF_1s gap with λ 125000	0.59	21.9
	nominal, HPF_1s gap with λ 400000	0.62	25.2
	real, HPF_1s gap with λ 25000	0.74	21.08
	real, HPF_1s gap with λ 125000	0.78	28.84(**)
	real, HPF_1s gap with λ 400000	0.79	34.79(**)
	nominal, HPF_2s gap with λ 25000	0.66	14.74
	nominal, HPF_2s gap with λ 125000	0.66	12.36
	nominal, HPF_2s gap with λ 400000	0.61	9.32
	real, HPF_2s gap with λ 25000	0.65	10.70
	real, HPF_2s gap with λ 125000	0.66	9.91
	real, HPF_2s gap with λ 400000	0.63	8.75
HH credit	1y growth	0.74	0.12
HH credit to non-mining GDP ratio	real, HPF_1s gap with λ 25000	0.77	18.95
	real, HPF_1s gap with λ 125000	0.80	26.48(**)
	real, HPF_1s gap with λ 400000	0.80	32.67(**)
	real, HPF_2s gap with λ 25000	0.68	11.63
	real, HPF_2s gap with λ 125000	0.66	9.99
	real, HPF_2s gap with λ 400000	0.62	8.34
DSR	nominal, HPF_2s gap with λ 25000	0.39	-6.13e-08
	nominal, HPF_2s gap with λ 125000	0.49	-2.61e-07
	nominal, HPF_2s gap with λ 400000	0.53	-3.82e-07

, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

While indicators related to the private sector exhibit relatively lower significance compared to credit development variables, the overall conclusion for this group remains consistent with existing literature. For instance, the real household debt-to-GDP gap, when filtered using the one-sided HP filter, outperforms other indicators within the private sector category.

Table 6: External Imbalances Results

Indicator	Transformation	Univariate AUROC	Logit coef
Current account to GDP ratio	$\frac{\text{Average of current account (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.98	205.1(***)
Capital account to GDP ratio	$\frac{\text{Average of capital account (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.93	117.6(***)
BoP to GDP ratio	$\frac{\text{Average balance of payment (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.76	14.56(**)
Export_price	YoY change	0.79	4.09(**)

, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

Interestingly, variables related to external imbalances have proved highly effective as early warning indicators in this analysis. Notably, the current account-to-GDP ratio exhibits exceptional predictive performance, achieving an AUROC score of 0.98—making it one of the most reliable indicators for signaling potential banking crises. Similarly, the capital account-to-GDP ratio also demonstrates a high AUROC score. Importantly, both indicators yield statistically significant coefficients in the logit regression model, reinforcing their robustness and relevance in identifying systemic vulnerabilities.

Table 7: Potential Mispricing of Risk

Indicator	Transformation	Univariate AUROC	Logit coef
Top20 index	YoY change	0.77	0.25

, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

While mispricing risk is often a critical factor in the build-up of financial vulnerabilities in advanced economies, this appears to be less relevant in the context of Mongolia. The country's financial system is heavily bank-centric, with the capital markets contributing only 0.6% of total financial system assets. As a result, market-based indicators of mispricing have limited applicability in detecting systemic risks in Mongolia.

Table 8: Strength of Bank Balance Sheets

Indicator	Transformation	Univariate AUROC	Logit coef
Equity multiplier		0.14	-1.1 (***)
Leverage		0.14	-1.1 (***)
Loan to deposit ratio		0.81	11.79(***)

, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

Table 8 presents the performance of selected indicators related to the strength of bank balance sheets. Among the variables assessed, the loan-to-deposit ratio may emerge as a potentially effective early warning indicator of banking sector distress. Specifically, it records a relatively high AUROC score of 0.81, indicating strong discriminatory power in the univariate setting. Moreover, the logit regression coefficient is large and statistically significant at the 1% level, further confirming its predictive value. In contrast, the equity multiplier and leverage ratio demonstrate weak performance, both yielding low AUROC scores (0.14) and negative coefficients, despite being statistically significant.

Table 9: Other Potential Indicators

Indicator	Transformation	Univariate AUROC	Logit coef
M2	YoY change	0.81	5.55(**)
Budget balance-to-GDP ratio	$\frac{\text{Cumulative budget balance (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.96	31.13(***)
Budget expenditure-to-GDP ratio	$\frac{\text{Cumulative budget expenditure (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.11	-60.0(***)

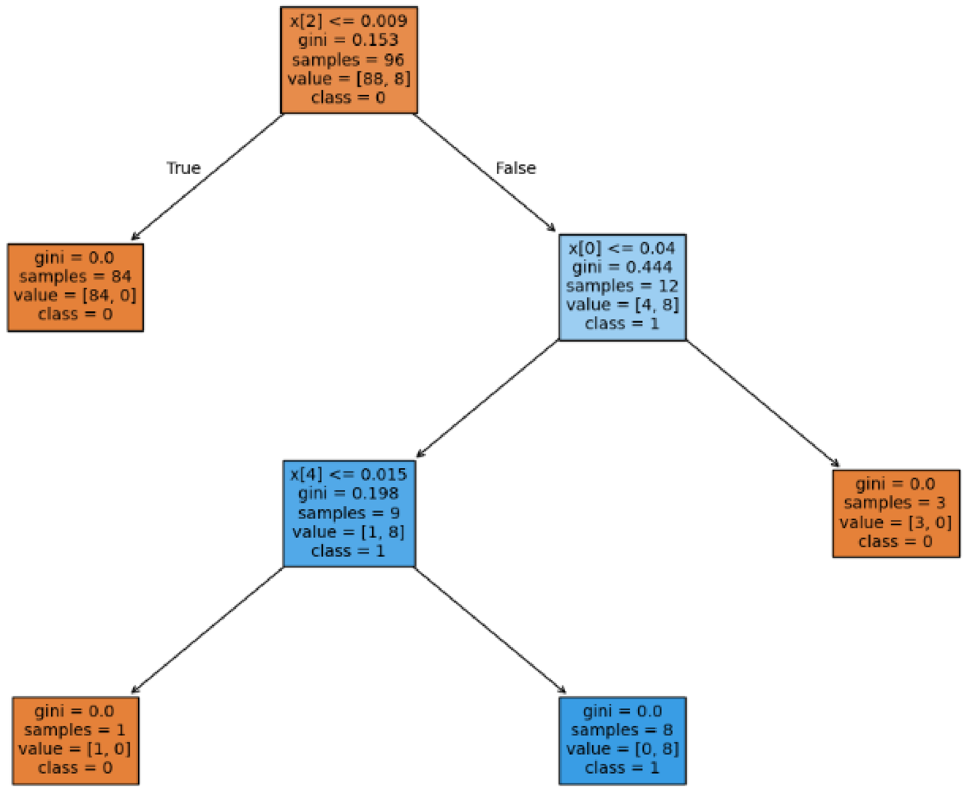
, ** and * indicate statistical significance at the 10 %, 5 % and 1 %-level*

The results of additional macro-financial indicators' evaluation indicate that both budget balance-to-GDP ratio and M2 growth exhibit strong predictive power. In particular, the budget balance-to-GDP ratio, computed as the cumulative budget balance over the past four quarters relative to cumulative GDP, achieves an AUROC score of 0.96 and a statistically significant logit coefficient of 31.13 at the 1% level, making it one of the most robust early warning indicators across all categories (see **Table 9**). This suggests that procyclical fiscal policy, especially during periods of economic expansion, may contribute to excessive credit growth or heightened risk-taking within the banking sector. In economies heavily dependent on volatile revenue sources – such as commodity exports – sudden external shocks can swiftly weaken the fiscal position, in turn placing stress on financial institutions.

Taken together, the results of the signaling and logit approaches consistently highlight a small set of indicators with high predictive value. In particular, the real credit-to-GDP gap, calculated using the one-sided HP filter, remains a strong predictor of financial distress. Complementary indicators – including loan-to-deposit ratio, current account-to-GDP ratio, and budget balance-to-GDP ratio – demonstrate similar predictive performance, reinforcing their suitability for inclusion in early warning models and countercyclical capital buffer frameworks.

6.1.2. Decision tree model

Figure 4: Decision tree model result



The results from the decision tree model indicate that the current account-to-GDP ratio (*x[2]*) serves as the most informative early warning indicator. Specifically, when the value of this indicator exceeds 0.009, it signals an elevated likelihood of a banking crisis occurring within the subsequent 4 to 12 quarters. Following this, the model identifies the real credit-to-GDP gap (*x[0]*) as the second most relevant variable. A breach of the 0.04 threshold in this indicator reinforces the signal of potential distress. Lastly, the budget balance-to-GDP ratio (*x[4]*) emerges as a supplementary indicator; when this ratio exceeds 0.015, it adds further weight to the probability of an upcoming crisis.

As of 2024, the current account-to-GDP ratio remains at -1.8%, which is well below the identified threshold, suggesting no immediate signal of a banking sector distress in the medium term. Among the remaining indicators, the real credit-to-GDP gap has nearly reached its threshold, returning to levels observed in previous peaks, while the budget balance-to-GDP ratio has already exceeded its corresponding threshold. Nevertheless, since the primary trigger – the current account variable – has not signaled distress, the model does not currently indicate an elevated risk of a banking crisis within the next 4 to 12 quarters (see **Figures 7, 8** and **9** in Appendix).

6.1.3. Robustness checks

Alternative country's case ***(Kazakhstan)***

A key limitation of developing early warning models using a single-country approach is the relatively small number of crisis episodes available, which may reduce the reliability of statistical inferences regarding the performance of potential indicators. As noted by Škrinjarić (2022), such limitations raise concerns about the robustness and generalizability of results derived solely from country-specific analyses. To address this challenge, we have extended our analysis by incorporating data from a comparable country that shares similar economic structures, financial structures, as well as geographic characteristics, with Mongolia. Among the potential candidates, Kazakhstan is selected as the most suitable comparator. Both Mongolia and Kazakhstan are landlocked, resource-dependent economies with bank-dominated financial systems, and each has undergone post-Soviet economic transitions, making them institutionally and structurally comparable for the purpose of robustness testing.

In the Mongolian case, the credit-to-GDP gap, current account-to-GDP ratio, and budget balance-to-GDP ratio are identified as the most effective early warning indicators. We have sought to examine the performance of these same indicators in the case of Kazakhstan. However, due to data limitations, consistent quarterly data on the budget balance-to-GDP ratio is not available for Kazakhstan. As a result, the robustness check focuses on the remaining two indicators – credit-to-GDP gap and current account-to-GDP ratio – which are evaluated using the same methodological frameworks applied to Mongolia.

Table *10*: Potential Early Warning Indicators for Kazakhstan

Indicator	Transformation	Univariate AUROC	Logit coef
Credit to GDP ratio	nominal, HPF_1s gap with λ 25000	0.90	38.79(***)
	nominal, HPF_1s gap with λ 125000	0.95	38.72(***)
	nominal, HPF_1s gap with λ 400000	0.97	42.79(***)
	nominal, HPF_2s gap with λ 25000	0.79	11.77(**)
	nominal, HPF_2s gap with λ 125000	0.84	10.51(***)
	nominal, HPF_2s gap with λ 400000	0.84	9.49(***)
Current account to GDP ratio	$\frac{\text{Average of current accont (last 4 quarters)}}{\text{Cumulative GDP (last 4 quarters)}}$	0.57	6.37

The results indicate that the credit-to-GDP gap, when computed using the one-sided HP filter, outperforms its two-sided counterpart in predicting banking crises. Specifically, applying a smoothing parameter of 400,000 yields an AUROC score of 0.97, suggesting a high level of predictive accuracy and confirming its suitability as a leading early warning indicator. In contrast, the current account-to-GDP ratio does not demonstrate statistical significance in the case of Kazakhstan, suggesting limited predictive value in this context. Visual inspection of the corresponding time series (see **Figure 5** and **6**) further supports these findings: the credit-to-GDP gap displays a pronounced upward trajectory beginning approximately 10 quarters prior to the onset of the crisis, thereby reinforcing its role as a reliable and timely signal of emerging systemic risk within Kazakhstan's banking sector.

Figure 5: Dynamic of credit-to-GDP gap

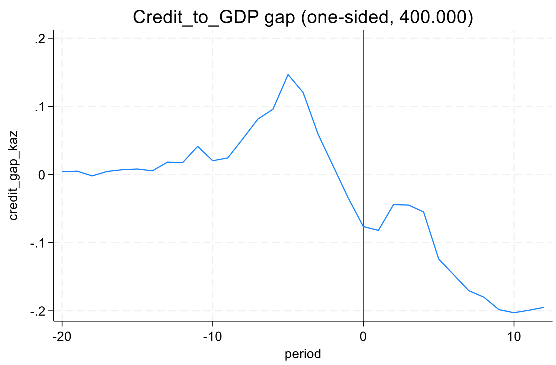
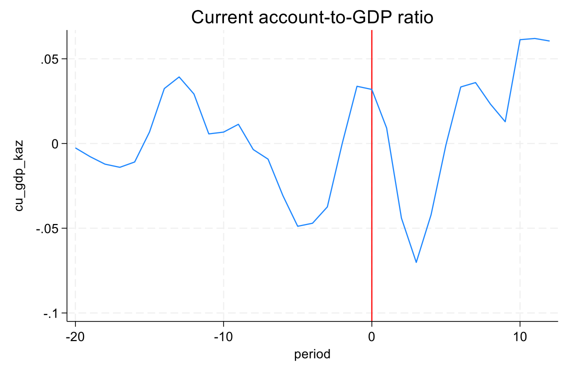


Figure 6: Dynamic of current account-to-GDP ratio



Note: The red line indicates the beginning of the crisis

Changing evaluation period

An additional approach to evaluating the robustness of early warning indicators involves varying the signaling horizon – that is, the length of time between the issuance of a signal and the onset of a crisis. According to Drehmann and Juselius (2014), an indicator is considered stable and reliable if its predictive power intensifies as the crisis approaches. In this context, a strong indicator should consistently produce more accurate and timely signals when the evaluation window is moved closer to the crisis event. This method allows for the assessment of an indicator's temporal consistency, which is essential for effective implementation in dynamic macroprudential surveillance frameworks.

Our findings indicate that the credit-to-GDP gap, household credit-to-GDP gap, current account-to-GDP ratio, year-on-year export price growth, and M2 growth exhibit temporal stability, as evidenced by increasing AUROC scores as the evaluation horizon approaches the onset of the crisis. This pattern suggests that these indicators generate progressively stronger and more accurate signals closer to the crisis period, reinforcing their suitability as reliable components of an early warning system.

***Table** 11: Distance from Final Quarter of Evaluation Period to Crisis*

Indicators	Transformation	Distance to Crisis (in Quarters)					
		2	4	6	8	10	12
Credit-to-GDP gap	nominal, HPF_1s gap with λ 400000	0.72	0.65	0.65	0.68	0.75	0.81
	real, HPF_1s gap with λ 400000	0.93	0.83	0.75	0.67	0.67	0.73
Total credit	1y growth	0.78	0.73	0.68	0.66	0.69	0.78
HH credit-to-GDP gap	real, HPF_1s gap with λ 400000	0.86	0.79	0.72	0.65	0.64	0.64
HH credit	1y growth	0.76	0.74	0.70	0.71	0.73	0.80
Current account-to-GDP ratio	Average of current account (last 4 quarters) / Cumulative GDP (last 4 quarters)	1.00	0.98	0.96	0.90	0.84	0.77
Capital account-to-GDP ratio	Average of capital account (last 4 quarters) /Cumulative GDP (last 4 quarters)	0.90	0.93	0.95	0.98	0.99	0.87
Export_price	1y change	0.78	0.79	0.81	0.73	0.68	0.70
Loan to deposit ratio		0.87	0.81	0.76	0.73	0.75	0.72
M2	1y change	0.87	0.81	0.74	0.64	0.67	0.72
Budget balance to GDP ratio	Cumulative budget expenditure (last 4 quarters) / Cumulative GDP (last 4 quarters)	0.99	0.96	0.90	0.80	0.71	0.59

Note: The same evaluation horizon as used in Section 6.1.1 has been applied here

*Alternative Filtering Methods for calculating the **credit-to-GDP Gap***

Although the BIS considers the credit-to-GDP gap, calculated using the Hodrick-Prescott (HP) filter, as a cornerstone indicator for setting the CCyB, there are two key criticisms of this approach. The first is the normalization critique: researchers argue that the gap can be distorted by revisions to either credit or GDP data, potentially leading to misleading signals. Additionally, the gap may reflect movements in nominal GDP rather than changes in credit, thus signaling a crisis risk even when there is no excessive lending. The second critique concerns the long-run trend component, highlighting three issues: the start-point problem, the end-point problem, and the tendency to underestimate cyclical risk in certain periods (Jokipii et al. 2021).

To address these concerns while assessing the robustness of our findings, we applied a range of alternative filtering techniques – including the Butterworth, Christiano-Fitzgerald, Baxter and King, and Hamilton filters – to compute the credit-to-GDP gap. The performance of each filtering method was evaluated using both AUROC scores and logit regression coefficients, as summarized in **Table 12**.

Table *12*: AUROC and Logit Regression Results Using Alternative Filtering Methods

Indicators	AUROC[5] and logit coefficient									
	HP filter		Butterworth filter		Christiano-Fitzgerald filter		Baxter and King		Hamilton	
	AUROC	*Log.coef*	*AUROC*	*Log.coef*	*AUROC*	*Log.coef*	*AUROC*	*Log.coef*	*AUROC*	*Log.coef*
Credit-to-GDP gap, nominal	0.65[6]	9.58	0.65	5.38	0.17	-51.5	0.34	-387	0.73	8.39
Credit-to-GDP gap, real	**0.83**[7]	25.43(**)	0.78	13.78(**)	0.33	-10.16	0.45	-129.21	0.79	14.64(**)

The results indicate that the HP filter outperforms other filtering methods, particularly when applied to real (inflation-adjusted) credit data. The real credit-to-GDP gap derived from the HP filter achieved the highest AUROC score (0.83) and a statistically significant logit coefficient of 25.43, confirming its effectiveness as an early warning indicator. The Butterworth filter also produced reasonably strong results, with and AUROC of 0.78 and a significant logit coefficient. In contrast, the Christiano-Fitzgerald and Baxter-King filters yielded notably lower AUROC scores and unstable logit estimates, suggesting limited predictive value. Interestingly, Hamilton filter also performed well, achieving a relatively high AUROC (0.79) and a statistically significant logit coefficient for the real gap, indicating its potential as a viable alternative. Overall, while the HP filter remains the most effective method in out setting, the Hamilton and Butterworth filters may serve as credible alternatives, particularly when robustness across filtering techniques is desired.

6.2. Key Findings of the Panel Regression

This section presents the key empirical findings derived from the panel regression analysis, which investigates the relationship between changes in capital adequacy and bank lending activity. The analysis, based on comprehensive quarterly bank-level data, demonstrates that increases in capital adequacy requirements, as measured by the CAR, are associated with a contraction in lending. Specifically, the baseline regression results in Table 13 show that one percentage point increase in the CAR leads to a 0.738 percentage point decline in the loan-to-asset ratio, holding other factors constant. This finding is consistent with the theoretical expectation that stricter capital regulation – such as the CCyB – can have a moderating effect on credit supply by requiring banks to internalize more risk.

[5] Evaluation period is set between the 5th and 12th quarters prior crisis

[6] nominal, HPF_1s gap with λ 400000

[7] real, HPF_1s gap with λ 400000

Table *13*: Estimated Effects of Bank-Specific Variables on Loan Growth: Full Sample and Subsamples by Bank Asset Size

	Loans		
	All banks	Large banks	Small banks
	(1)	**(2)**	**(3)**
CAR (-1)	-0.738***	-1.094**	-0.397**
	(0.189)	(0.268)	(0.0882)
capital (-1)	0.913***	0.422	0.193*
	(0.191)	(0.460)	(0.0486)
provision (-1)	0.906**	0.282	0.341*
	(0.358)	(1.143)	(0.0987)
net int. inc (-1)	1.948**	3.071*	0.501*
	(0.683)	(1.196)	(0.139)
profit (-1)	-0.359*	3.744*	-0.214
	(0.177)	(1.552)	(0.192)
cash (-1)	0.0547	5.952**	2.005
	(2.047)	(2.060)	(0.811)
deposit (-1)	0.0890	-0.125	0.314*
	(0.121)	(0.0981)	(0.0877)
log(asset) (-1)	0.0454	-0.0516**	-0.0594*
	(0.0280)	(0.0138)	(0.0167)
Fixed effects	Bank & time	Time	Time
N	465	316	145
R-squared	0.702	0.740	0.870

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The analysis further reveals heterogeneous effects by bank size. When the dataset is disaggregated into large and small banks, the magnitude of the negative relationship between capital adequacy and lending varies significantly. For large banks, the estimated coefficient is more negative, suggesting that they reduce lending more sharply in response to increased capital requirements. This may reflect their greater exposure to supervisory scrutiny, stronger incentives to maintain regulatory compliance, or more complex balance sheet structures that limit flexibility in adjusting capital rations without curbing credit. In contrast, smaller banks exhibit a weaker negative response, indicating that their lending behavior is less sensitive to changes in capital requirements. This distinction may stem from differences in regulatory pressure, internal capital buffers, or risk-taking incentives.

These results highlight the importance of accounting for institutional heterogeneity in the design and implementation of macroprudential policies. A one-size-fits-all approach may not yield uniform outcomes across banks of different sizes, and tailored policy calibration may be necessary to balance the goals of financial stability and credit provision across the banking system.

Table *14*: Extended Panel Regression Estimates: Testing Robustness with CAR Lags and Macroeconomic Variables

	Loans		
	(1)	**(4)**	**(5)**
CAR (-1)	-0.738***	-0.596**	-0.757**
	(0.189)	(0.196)	(0.263)
CAR (-2)		-0.231***	
		(0.0372)	
Budget bal/GDP (-1)			0.289***
			(0.0534)
Current acc/GDP (-1)			-0.153
			(0.196)
Real GDP qoq (-2)			-0.000606
			(0.000701)
China GDP (-2)			0.00529***
			(0.00106)
Foreign exchange (-1)			0.206**
			(0.0719)
capital (-1)	0.913***	0.959***	0.855***
	(0.191)	(0.206)	(0.240)
provision (-1)	0.906**	0.807**	0.603
	(0.358)	(0.324)	(0.421)
net.int.inc (-1)	1.948**	1.621***	0.466*
	(0.683)	(0.419)	(0.204)
profit (-1)	-0.359*	-0.462**	-0.256
	(0.177)	(0.146)	(0.375)
cash (-1)	0.0547	0.521	1.800
	(2.047)	(2.137)	(1.561)
deposit (-1)	0.0890	0.0696	0.0248
	(0.121)	(0.0963)	(0.113)
log(asset)	0.0454	0.0286	-0.0197
	(0.0280)	(0.0235)	(0.0190)
Fixed effect	Bank & time	Bank & time	Bank
N	465	458	439
R-squared	0.702	0.707	0.596

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To strengthen the empirical validity of this relationship, we extend the model by introducing alternative lags of the CAR and by incorporating macroeconomic control variables identified as significant predictors in the early warning signaling and decision-tree analyses. These variables include the budget balance-to-GDP ratio and the current account balance, which serve as proxies for the broader economic environment. The dependent variable continues to be defined as the loan-to-asset ratio, a standardized indicator of lending intensity across banks. All explanatory variables are lagged by one or two quarters to mitigate potential simultaneity bias and improve causal inference.

In Regression (**4**) of extended estimates (**Table14**), the coefficient of CAR with 2 quarterly lags is negative and statistically significant, indicating that the effects of capital requirements persist over time. This delayed response suggests that increases in regulatory capital may not immediately affect lending decisions but exert a gradual and lasting dampening effect on credit supply. Hence, raising CAR requirements can reduce lending not only in the immediate quarter but also in subsequent periods, highlighting the temporal dimension of capital regulation's influence on bank behavior.

Regression (**5**) introduces key macroeconomic control variables, including the budget balance-to-GDP ratio, current-account-to-GDP ratio, real GDP growth, China's GDP growth, and the foreign exchange rate. Importantly, the coefficient for CAR remains within the range observed in the main specification (Regression (**1**)), underscoring the robustness of the core result. Among the macroeconomic variables, the budget balance-to-GDP ratio is positive and statistically significant, implying that fiscal surpluses are associated with higher lending, potentially due to improved creditworthiness and reduced sovereign risk perceptions. Likewise, China's GDP growth exhibits a positive and significant coefficient, reflecting Mongolia's strong economic interdependence with China. As Mongolia's largest trading partner, China's economic expansion contributes to improved fiscal revenues and export performance, which in turn supports domestic credit growth.

The foreign exchange rate also emerges as a positive and significant determinant of lending, possibly indicating that a stronger domestic currency improves the external balance and enhances banks' confidence in credit expansion. In contrast, the coefficients for the current account-to-GDP ratio and real GDP growth are statistically insignificant, suggesting that these variables have a limited direct impact on short-term bank lending behavior within the estimation horizon.

To provide a more nuanced understanding of how capital requirements interact with macroeconomic conditions to influence bank lending behavior, we further extend the previous regression analysis by incorporating interaction terms between CAR and macroeconomic threshold indicators identified through the decision-tree model. **Table 15** presents the results of these extended panel regressions, which evaluate whether the impact of CAR on lending is conditional upon macroeconomic environments. The decision-tree algorithm identified three key threshold indicators most relevant to the likelihood of financial system distress: the current account-to-GDP ratio, the budget balance-to-GDP ratio, and the real credit-to-GDP gap. For each indicator, values exceeding the empirically derived threshold are determined and used to construct the respective interaction terms with CAR in the regression models.

Across all model specifications, the main effect of lagged CAR remains negative and statistically significant at the 1% level, with coefficients ranging from -0.722 to -0.740. This result corroborates the baseline findings reported in **Table 13** and **14**, confirming that higher regulatory capital requirements are associated with a reduction in bank lending.

In Regression (**7**), the interaction between CAR and a current account-to-GDP ratio above the threshold value of 0.009 is positive and statistically significant at the 5% level. This suggests that when the external balance is in surplus, the constraining effect of CAR on lending is partically offset, potentially due to improved investor confidence, lower funding costs, or greater external stability. Similarly, Regression (**9**) indicates that the interaction between CAR and a budget surplus exceeding its decision-tree threshold is positive and statistically significant at the 10% level. This finding implies that in fiscal environments characterized by strong public finances, the adverse effect of capital regulation on bank credit supply is attenuated, possibly due to lower perceived sovereign risk or more favorable domestic liquidity conditions.

These interaction effects highlight the importance of macroeconomic context in shaping the transmission of capital regulation, suggesting that CCyB may be more effective when implemented in conjunction with supportive macroeconomic conditions. Moreover, they underscore the value of incorporating early warning signals and threshold-based indicators into the design of dynamic capital regulation frameworks tailored to small, open, and bank dominated economies such as Mongolia.

Table 1515: Extended Interaction Effects Between Capital Adequacy and Macroeconomic Conditions on Bank Lending

	Loans					
	(6)	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
CAR (-1) x > Median Current acc/GDP (-1)	0.00315					-0.00779
	(0.0245)					(0.0335)
CAR (-1) x > Threshold Current acc/GDP (-1)		0.231**				
		(0.0795)				
CAR (-1) x > Median Budget bal/GDP (-1)			0.0575			0.0595
			(0.0459)			(0.0532)
CAR (-1) x > Threshold Budget bal/GDP (-1)				0.111*		
				(0.0505)		
CAR (-1) x < Median Real GDP (-1)					-0.00453	-0.00522
					(0.0505)	(0.0505)
CAR (-1)	-0.740***	-0.733***	-0.730***	-0.724***	-0.736***	-0.722***
	(0.194)	(0.187)	(0.195)	(0.189)	(0.175)	(0.196)
capital (-1)	0.914***	0.870***	0.883***	0.865***	0.914***	0.882***
	(0.191)	(0.195)	(0.199)	(0.193)	(0.195)	(0.207)
provision (-1)	0.905**	0.924**	0.962**	0.939**	0.902**	0.962**
	(0.358)	(0.352)	(0.345)	(0.353)	(0.332)	(0.328)
net.int.inc (-1)	1.950**	2.013**	1.993**	2.143**	1.953**	1.996**
	(0.683)	(0.672)	(0.661)	(0.649)	(0.723)	(0.701)
profit (-1)	-0.362*	-0.314	-0.320*	-0.344*	-0.368**	-0.323**
	(0.172)	(0.169)	(0.159)	(0.175)	(0.120)	(0.124)
cash (-1)	0.0565	0.326	0.169	0.261	0.0479	0.161
	(2.046)	(2.190)	(2.152)	(2.174)	(2.071)	(2.176)
deposit (-1)	0.0889	0.0794	0.0908	0.0862	0.0891	0.0913
	(0.122)	(0.117)	(0.121)	(0.115)	(0.120)	(0.122)
log(asset) (-1)	0.0452	0.0433	0.0474	0.0444	0.0453	0.0478
	(0.0285)	(0.0269)	(0.0291)	(0.0269)	(0.0282)	(0.0305)
Fixed effects	Bank & time	Bank & time	Bank & time	Bank & time	Bank & time	Bank & time
N	465	465	465	465	465	465
R-squared	0.702	0.706	0.704	0.705	0.702	0.704

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CONCLUSION

Mongolia's economy remains structurally vulnerable to external shocks due to its heavy reliance on commodity exports. Historically, favorable external conditions – often driven by elevated commodity prices – have encouraged procyclical fiscal and monetary policies, which, while supportive in the short term, have often undermined long-term macroeconomic and financial stability. These recurring patterns highlight the urgent need for a countercyclical policy approach to strenghten economic resilience and safeguard financial stability.

This study contributes to these efforts by developing a tailored framework for implementing the countercyclical capital buffer (CCyB) in Mongolia's banking sector. It identifies early warning indicators of financial stress and empirically examines how capital adequacy affects bank lending behavior – two key components for operationalizing the CCyB effectively. The analysis finds that indicators such as the real credit-to-GDP gap, credit growth, current acount-to-GDP ratio, budget balance-to-GDP ratio, loan-to-deposit ration, and M2 growth display strong early warning capabilities. In particular, the current account and budget balance ratios perform robustly across both signaling and discrete choice models, offering a valuable addition to the early warning literature. These indicators tend to improve during commodity booms, supporting credit expansion, but deteriorate during external downturns, thereby tightening liquidity and exacerbating cyclical declines in lending.

The panel regression analysis further confirms the contractionary effects of higher capital requirements on bank lending. Specifically, a one-percentage-point increase in the capital adequacy ratio is associated with a 0.74 percentage-point decline in the loan-to-asset ratio, illustrating the contractionary impact of regulatory capital buffers on credit supply. This relationship is heterogeneous across bank size: large banks show a more substantial reduction in lending in response to increased capital requirements (1.09 percentage point decline), while the effect is more modest among small banks (0.40 percentage point decline). These results underscore the importance of considering institutional heterogeneity when designing and implementing capital-based macroprudential tools to ensure effectiveness without disproportionate impacts on different segments of the banking sector.

Despite these findings, the analysis faces limitations due to the relatively small number of crisis episodes in Mongolia. To partially mitigate this, Kazakhstan – an economy with similar structural features – was included in this study. Nonetheless, the limited frequency of systmic crises constrains the robustness of early warning models, reflecting a broader challenge in research focused on small, developing, commodity-dependent economies.

Future research can enhance the validity and scope of such analyses by incoporating a broader set of structurally similar economies. This would not only strengthen statistical robustness but also preserve contextual relevance. In addition, applying more advanced econometric techniques – such as Vector Error Correction Models, Autoregressive Distributed Lag frameworks, or Bayesian estimation – could uncover long-term and nonlinear relationships among macro-financial indicators. Greater sectoral disaggregation, especially in credit-related variables (e.g., household vs. corporate lending), can also refine early warning models and improve policy precision.

In sum, this study offers a data-driven, context-sensitive foundation for implementing the CCyB in Mongolia. By integrating international best practices with Mongolia's specific macro-financial dynamics, it enhances the toolkit for macroprudential policymaking and contributes to broader efforts to safeguard financial stability in Mongolia and other similar emerging market economies.

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APPENDICES

Figure 7:Current account to GDP ratio with threshold

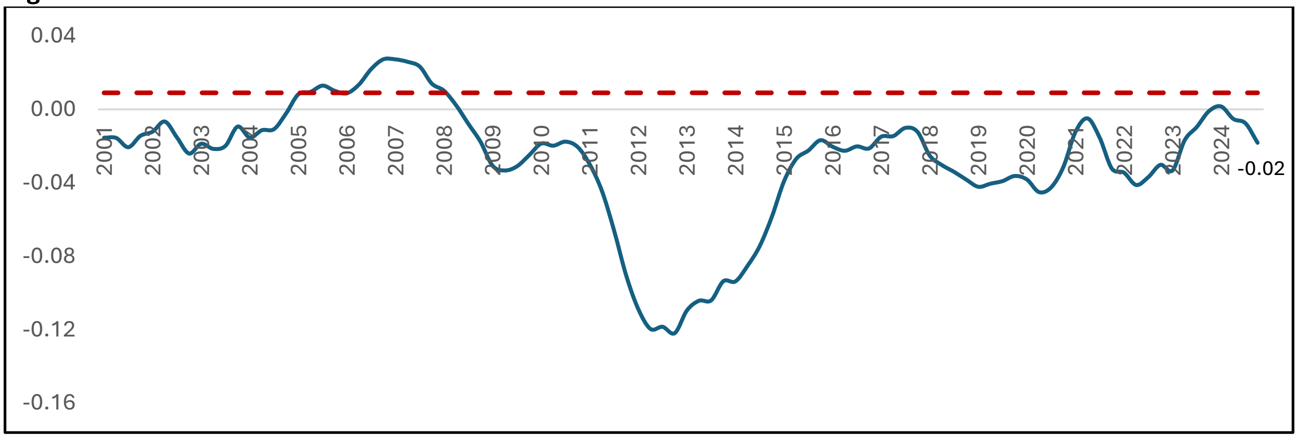


Figure 8:Credit to GDP gap with threshold

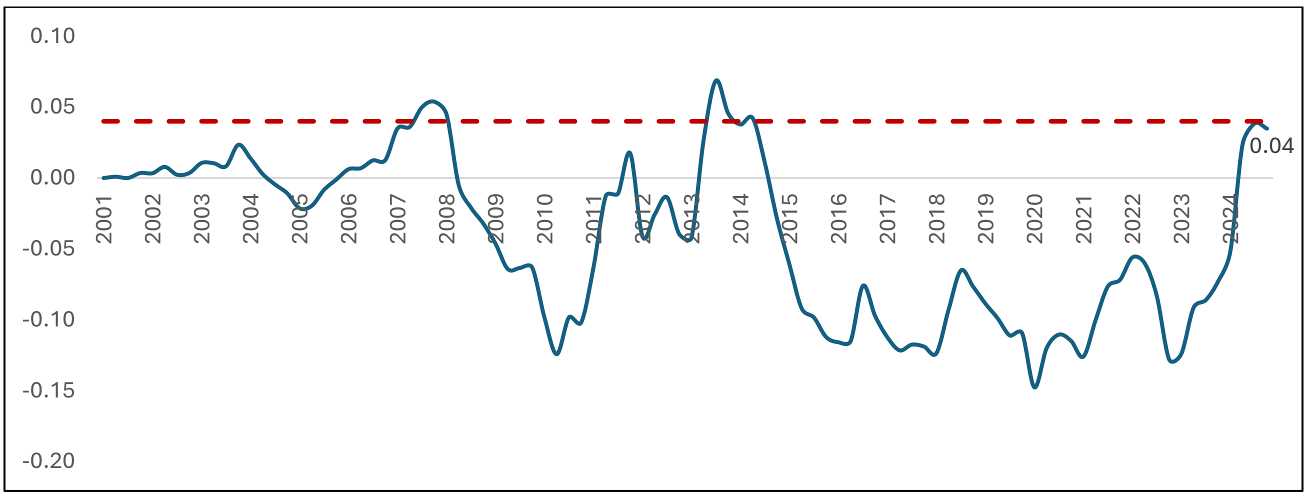
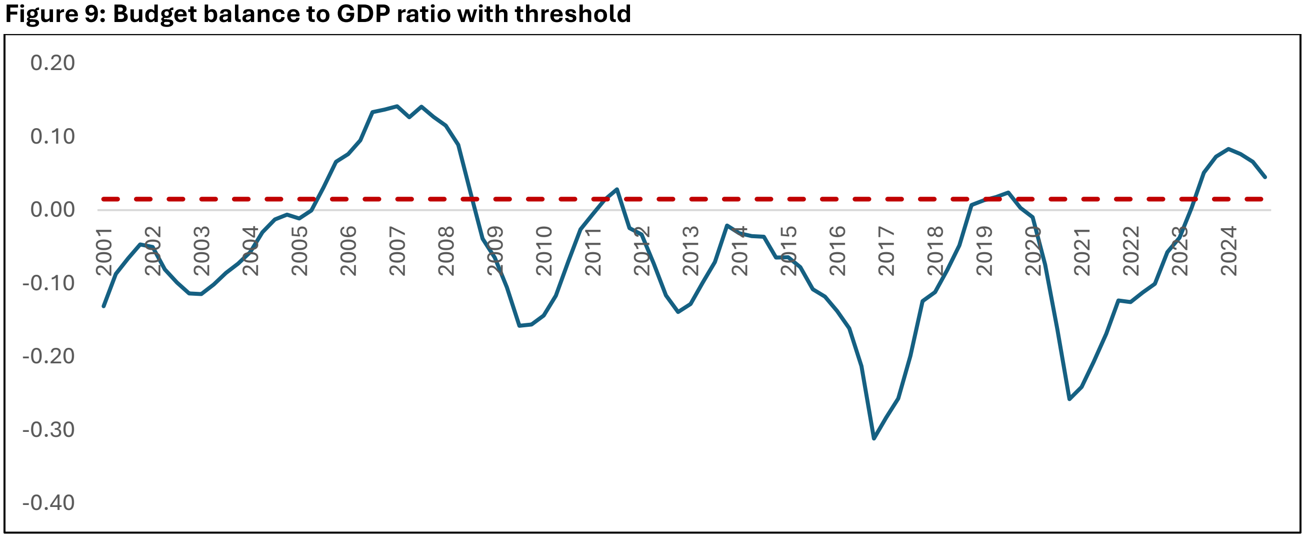
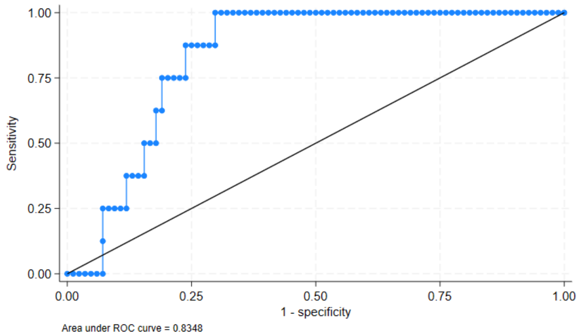


Figure 9: Budget balance to GDP ratio with threshold

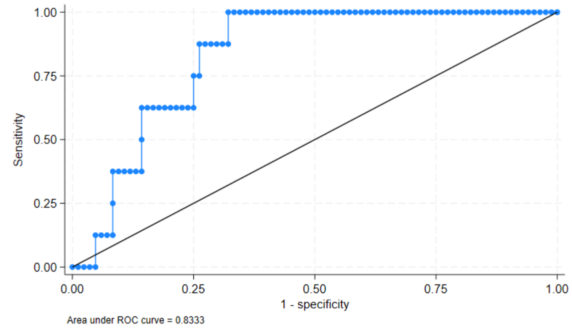


ROC curves (Credit development):

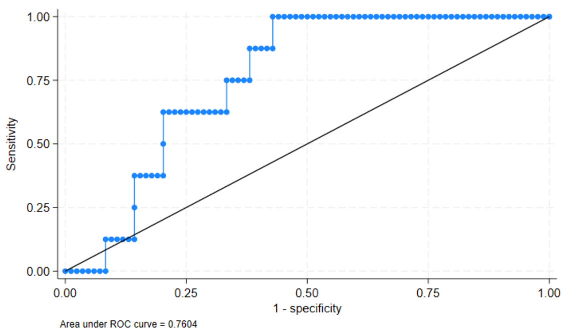
Real credit-to-nonmining GDP gap_1s_400000



Real credit-to-nonmining GDP gap_1s_400000_adjusted



Real credit-to-GDP gap_1s_25000



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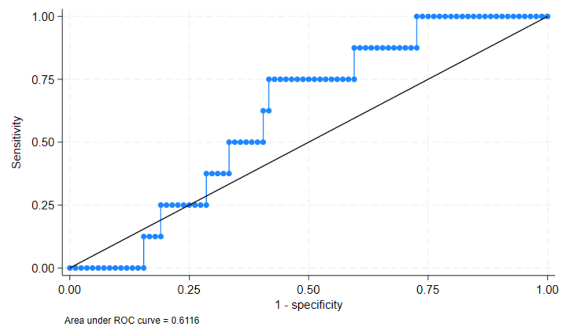

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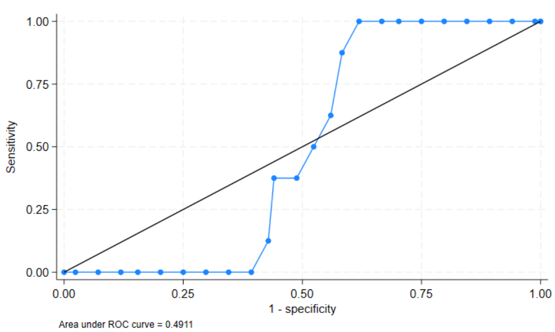
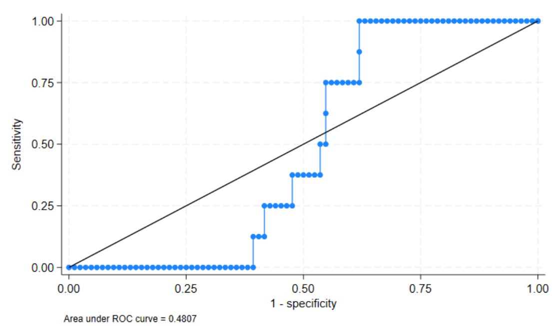
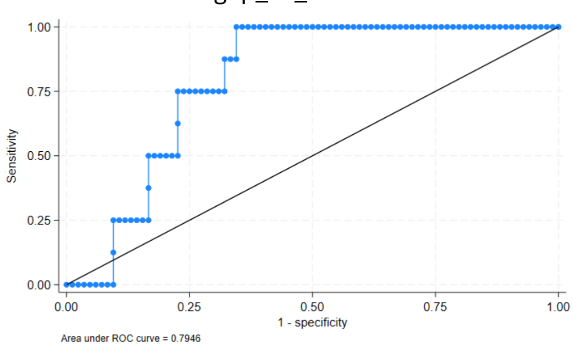


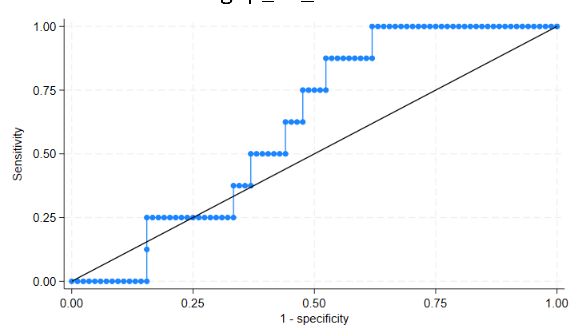
Nominal credit-to-GDP gap_2s_25000



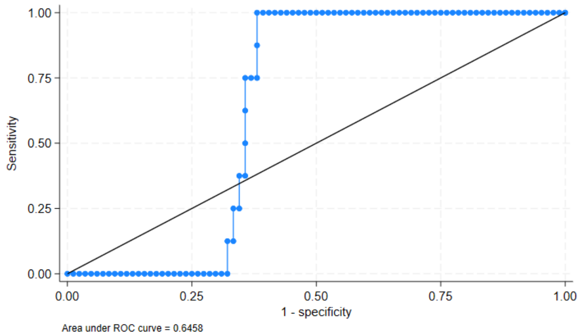
Real credit-to-GDP gap_1s_125000



Real credit-to-GDP gap_2s_125000



Nominal credit-to-GDP gap_1s_125000



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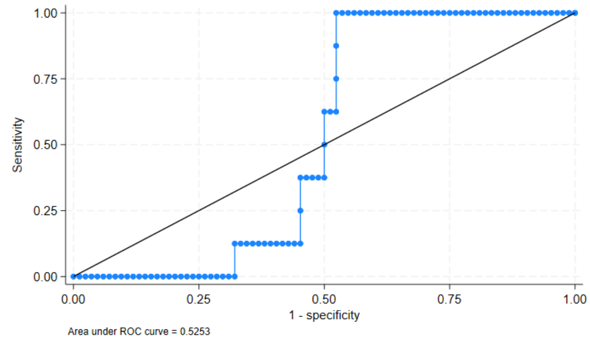
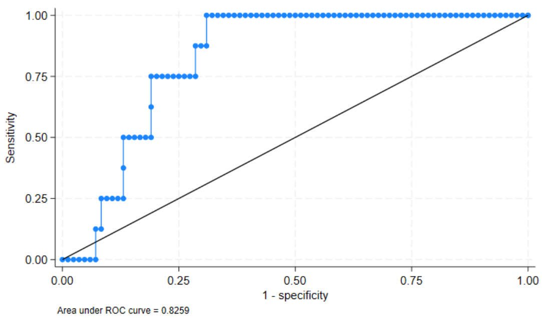
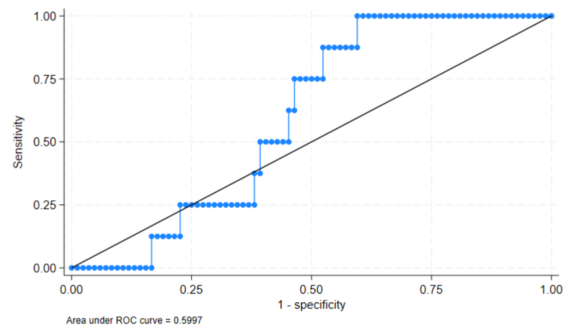


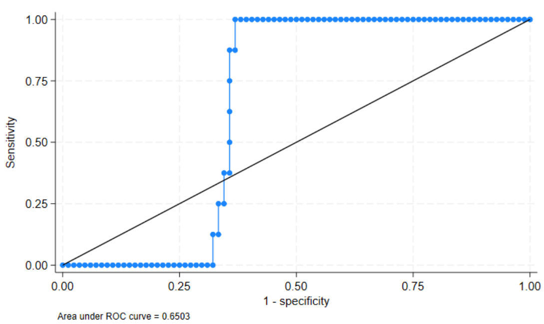
Real credit-to-GDP gap_1s_400000



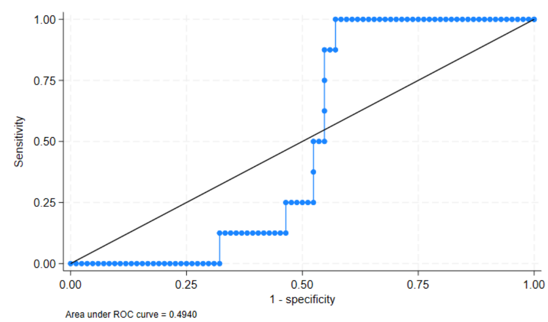
Real credit-to-GDP gap_2s_400000



Nominal credit-to-GDP gap_1s_400000

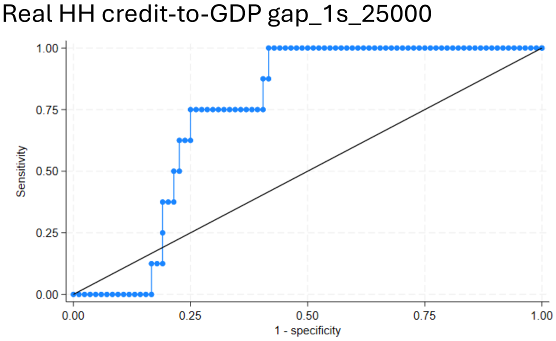


Nominal credit-to-GDP gap_2s_400000

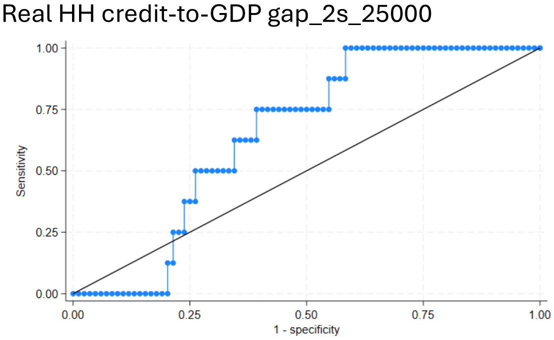


Private sector (ROC curves)

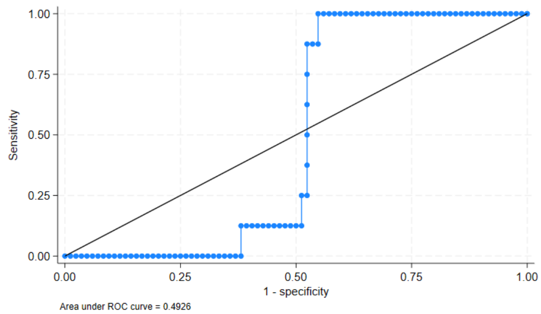
Real HH credit-to-GDP gap_1s_25000



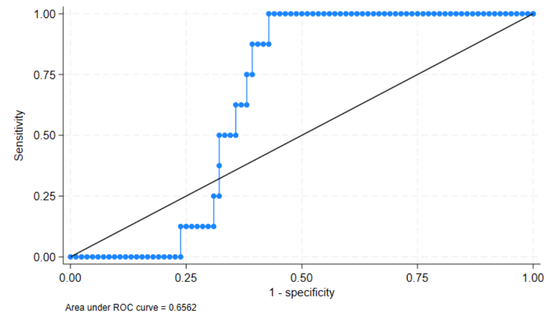
Real HH credit-to-GDP gap_2s_25000



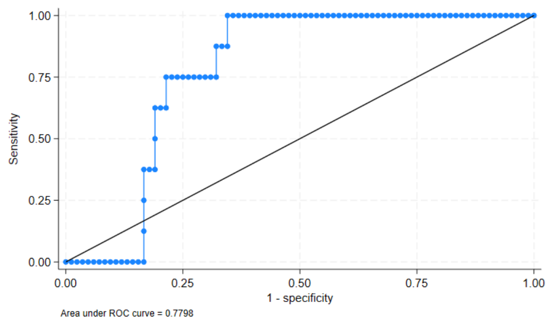
Nominal HH credit-to-GDP gap_1s_25000



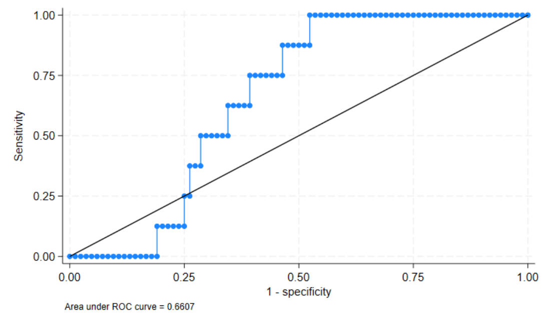
Nominal HH credit-to-GDP gap_2s_25000



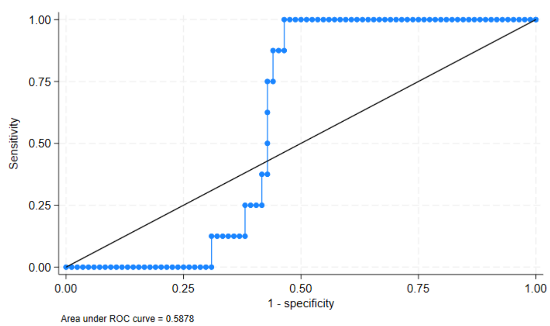
Real HH credit-to-GDP gap_1s_125000



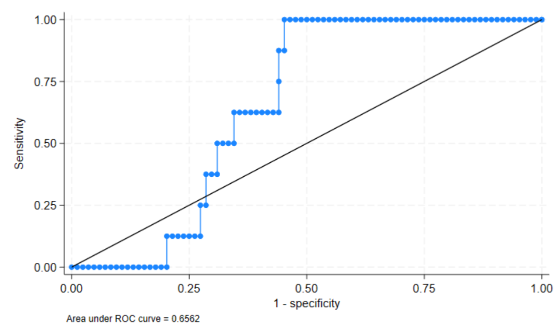
Real HH credit-to-GDP gap_2s_125000



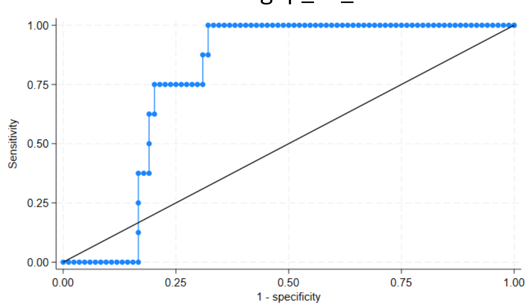
Nominal HH credit-to-GDP gap_1s_125000



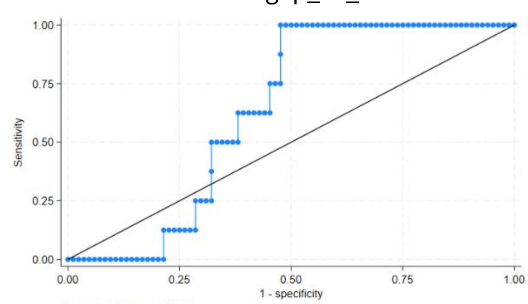
Nominal HH credit-to-GDP gap_2s_125000



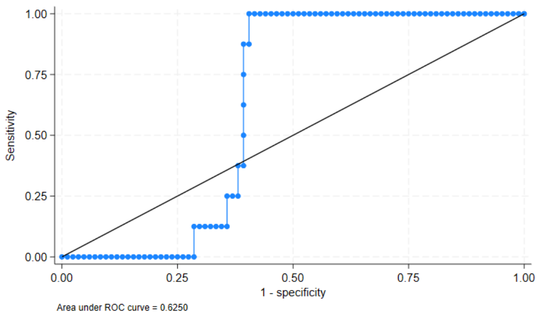
Real HH credit-to-GDP gap_1s_400000



Real HH credit-to-GDP gap_2s_400000



Nominal HH credit-to-GDP gap_1s_400000



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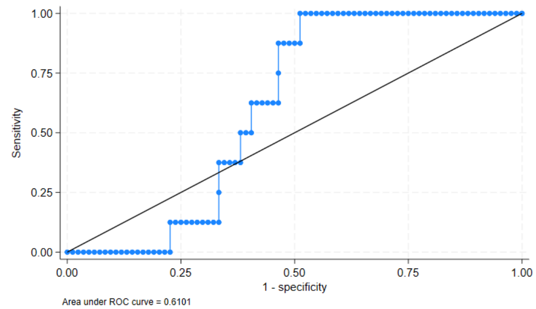
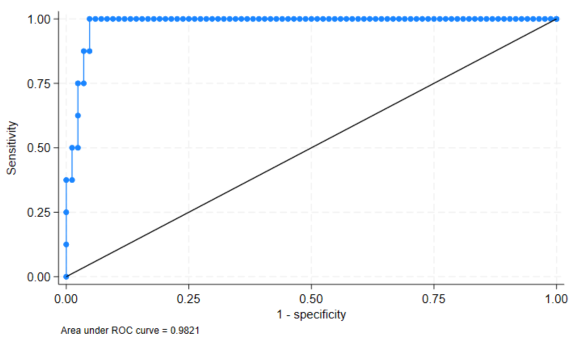
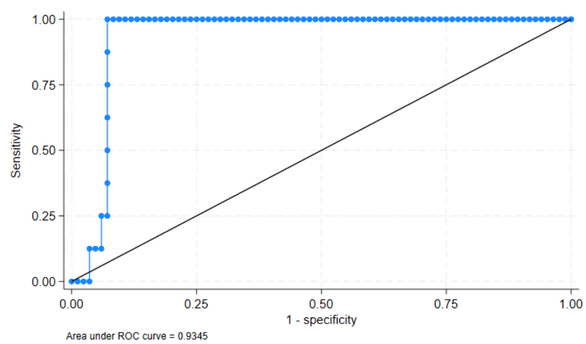


External imbalances (ROC curves)

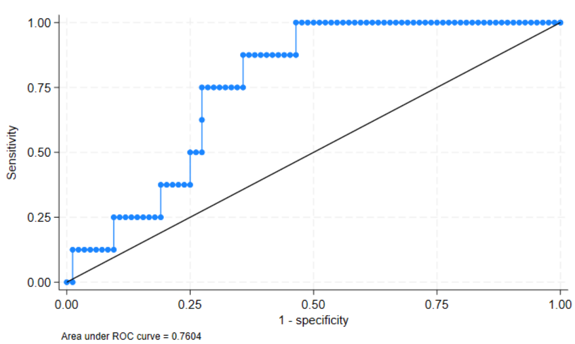
Current account-to-GDP ratio



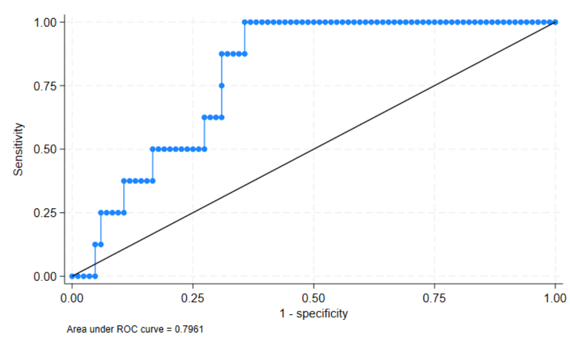
Capital account-to-GDP ratio



BoP-to-GDP ratio

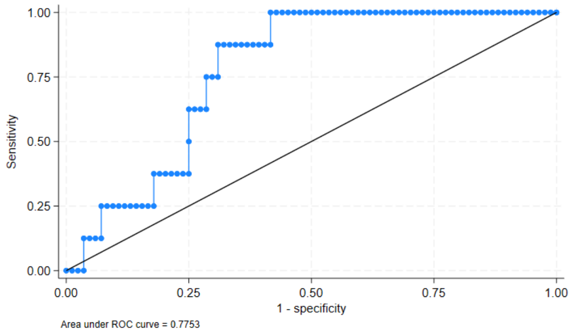


Export price growth

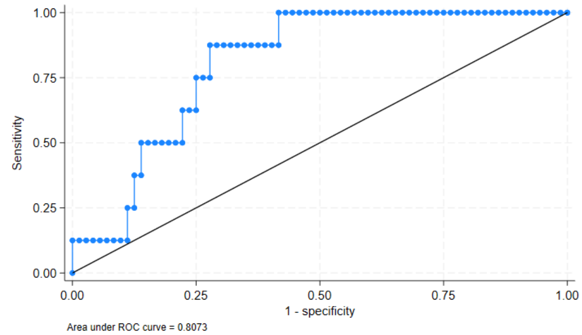


Strength of bank balance sheets and Mispricing risk (ROC curves)

Top 20 index growth

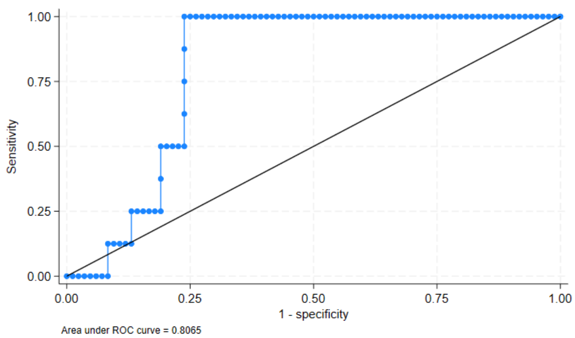


Loan to deposit ratio

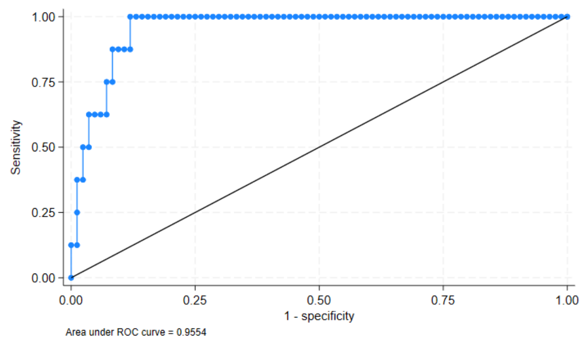


Other indicators (ROC curves)

M2 growth

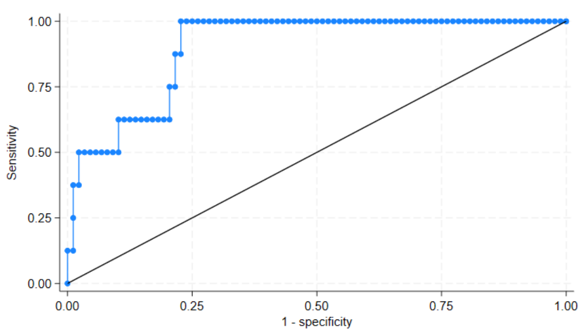


Budget balance-to-GDP ratio

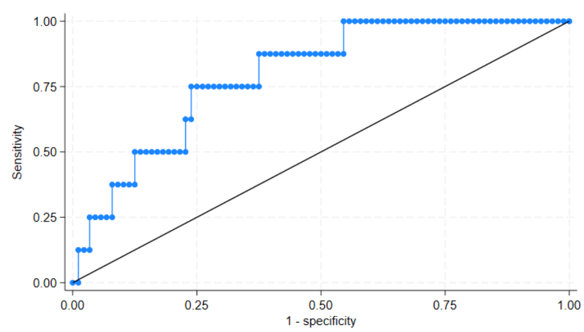


Other country's indicators (ROC curves)

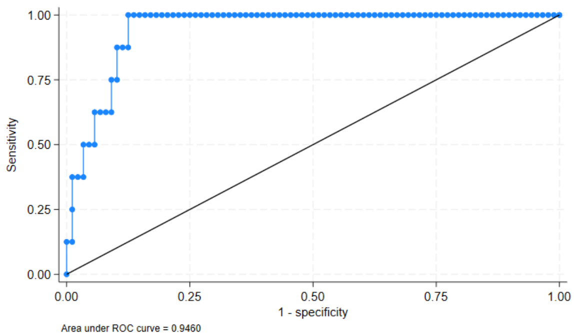
Credit-to-GDP gap_1s_25000



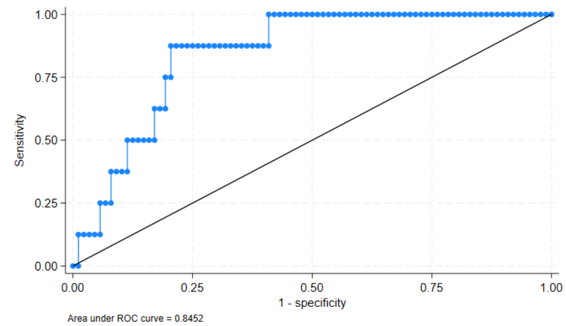
Credit-to-GDP gap_2s_25000



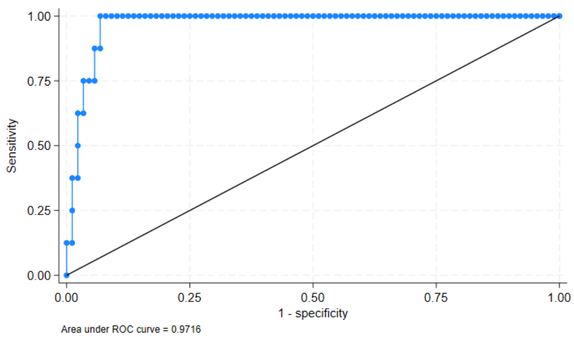
Credit-to-GDP gap_1s_125000



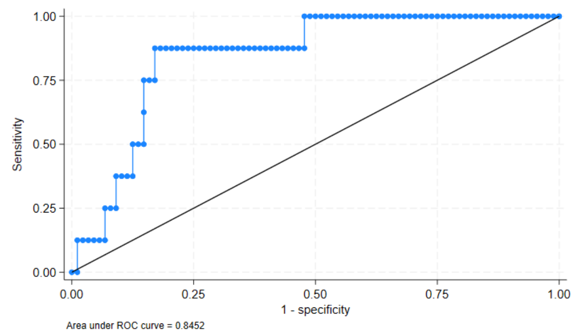
Credit-to-GDP gap_2s_125000



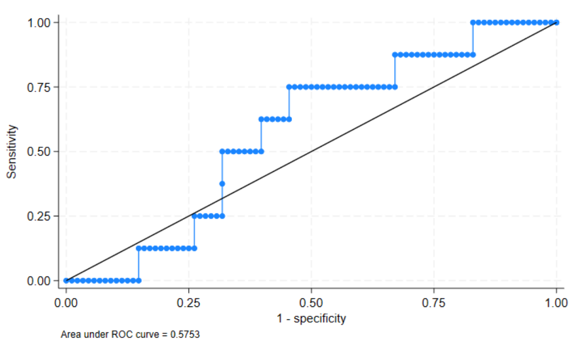
Credit-to-GDP gap_1s_400000



Credit-to-GDP gap_2s_400000



Current account to GDP ratio



Capital account to GDP ratio