Early Warning Indicators for the Slovak Banking Sector[1]

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Abstract

This paper tries to identify early warning indicators for the Slovak banking sector. The aim of the early warning indicators is to predict a build-up of imbalances or rising risks in the banking sector, using the credit-to-GDP gap as a proxy. Based on quarterly data from 1Q2003 to 4Q2023, we apply Bayesian model averaging (BMA) to explore the potential predictive power of 38 variables over a horizon of 4 to 12 quarters. The advantage of the BMA is that it accounts for uncertainty in the selection and combination of potential indicators. The results indicate the importance of both traditional early warning indicators – such as the unemployment rate, inflation, and interest rates – and uncertainty indicators, including sentiment-based survey data and media-derived policy uncertainty measures. Notably, the construction confidence indicator and the German Policy Uncertainty Index appear to indicate the potential for an increase in risk within the banking sector. Furthermore, our findings also underline the vulnerability of the Slovak banking sector to external shocks such as the COVID-19 pandemic, and highlight the role of household indebtedness in identifying emerging imbalances. These insights are relevant for macroprudential policy, particularly in the calibration of the countercyclical capital buffer.

Keywords: *early warning indicators, banking sector, financial imbalance, credit gap, Bayesian model averaging*

JEL Classification: C40, E44, G01, G21

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Introduction

Early warning systems for the banking system are models based on early warning indicators that are linked to past crises and risk factors. The objective of these systems is to draw attention to potential risks that may be on the rise or an imminent banking crisis. The creation of these systems is based on assumption of the existence of a causal relationship between crises and early warning indicators, as well as the capacity to identify these indicators in advance. From the perspective of banking supervision institutions, early warning systems represent models for the capture of the accumulation of various types of risks and imbalances within the banking system.

The growing interest in identifying early warning indicators, or in revealing the determinants of banking crises and factors that reduce the stability of the banking system, can be linked to two main factors. The first factor was the significant financial impact of banking crises and the costs of their resolution. This caused an increased interest in prediction models for banking crises among academics, regulatory and supervisory authorities, and international financial organizations (Goldenstein et al., 2000). The increased interest in the creation of prediction models emerged after the banking crises of the 1980s and 1990s. In the second half of the 1990s, there was a notable increase in the number of research papers that began to apply econometric analyses in the study of the determinants of banking crises and in the creation of their early warning models. The global financial crisis prompted a renewed interest among researchers, policymakers, and regulators in developing empirical models to identify the growing risk of a banking crisis.

This topic is also relevant in the context of the introduction of macroprudential policy instruments resulting from the CRD IV directive. When determining additional capital requirements, such as introduction of a countercyclical capital buffer, it is essential to have indicators that can identify the accumulation of systemic risks and financial imbalances that could threaten the stability of the banking system (NBS, 2014).

Many studies indicated that banking crises are associated with significant fiscal costs and an increase in public debt. A study by the International Monetary Fund (2014) found that for the period 1970 – 2011, the median cost of government interventions was 7% of GDP. In addition to the fiscal costs, banking crises have a negative impact on economic growth and present a risk not only to the country in which they originate, but also to other countries through contagion (Goldenstein et al., 2000).

The second reason for the increased interest in early warning indicators is the fact that, despite considerable efforts, it has not yet been possible to create an early warning model that would be 100% reliable in predicting potential banking crises.

This reason is also related to the very nature of banking crises. The creation of an early warning model for banking crises is challenging, given that such crises are rare events with diverse causes and effects. Thus, the development of early warning models has been a continuous process, in parallel with the increasing number of banking crises. Therefore, it is more challenging to assess the predictive efficacy of early warning systems, given that they are founded upon different sources of banking crises, or use distinct dependent variables and methodologies.

The goal of this paper is to propose early warning model which could help to predict potential issues in the Slovak banking sector. Slovakia, a member of the Eurozone and the OECD, underwent a transition process following the dissolution of the communist regime. This process was characterized by the restructuring of the banking sector, privatization, financial liberalization, the development of the property market and other transformation processes. Although a banking crisis has not occurred in Slovakia since the restructuring of the banking sector, the country's financial sector has nevertheless been exposed to certain vulnerabilities. During the global financial crisis (2008 – 2009), the Slovak financial sector was indirectly affected as a result of the economic downturn and rising unemployment, given that Slovakia is a highly export-dependent economy. In 2009, the Slovak banking sector was confronted with a series of challenges, including a decline in credit growth, a deterioration in asset quality within banking balances, a reduction in the profitability of banks, and an increase in credit risks. Notwithstanding the aforementioned risks, domestic banking institutions were, at the time, in a relatively favorable financial position to withstand such challenges (Financial stability report of the NBS, 2009 and 2010). The euro area sovereign debt crisis has had adverse effects not only on the Slovak real economy but also on the country's financial stability. While the credit risk was identified as the primary concern for the banking sector as a whole, macro stress testing showed that the Slovak banking sector remained resilient to shocks, predominantly due to the presences of considerable capital buffers and the limited reliance of domestic banks on external funding (Financial stability report of the NBS, 2011 and 2012).

In the aftermath of the global financial crisis, the banking sector exhibited a strong credit growth in the environment of low interest rates. Rising household indebtedness emerged as a significant risk factor for financial stability, leading to the implementation of macroprudential measures designed to tighten the conditions for new lending to households (Financial stability report of the NBS, 2020). The banking sector demonstrated resilience during the COVID-19 pandemic and went through without significant adverse consequences. Nevertheless, there was a potential threat emerging from an increase in the non-performing loan ratio among banks in Slovakia. However, the provision of credit and financial services remained uninterrupted. Following the coronavirus crisis, the Slovak banking sector has faced a number of new challenges and risks, predominantly originating from inflation, the war in Ukraine, elevated energy prices and the prevailing climate of economic uncertainty. Nevertheless, the capital position of the Slovak banking sector has remained robust, while the National Bank of Slovakia introduced additional lending regulations for households (Financial stability report of NBS, 2021 and 2022).

We try to identify early warning indicators that would signal the growing financial imbalances in the banking system, which could threaten its stability if unchecked, rather than predicting banking crises per se. We use the credit-to-GDP gap indicator to capture the build-up of financial imbalances. This indicator, the so-called Basel gap, has been advocated as a useful measure of credit excessiveness and cyclical risk (Borio and Drehmann, 2009; Basel Committee on Banking Supervision, 2010; Alessi and Detken, 2011; Drehmann et al., 2011; Detken et al., 2014). It was therefore used as the dependent variable in the model. However, we use an adjusted version of the credit-to-GDP gap in order to mitigate the main shortcomings associated with the estimation of the long-term trend. The independent variables in the model were potential indicators collected from different sectors. We focus on a country-specific early warning system. Barrell et al. (2010) and Davis et al. (2011) suggest that specification of the early warning model should take into account the heterogeneity of the economy and banking sector. Similarly to Koštálová et al. (2021), we assume that a single-country study is recommended from a policy maker's point of view and enables exploration of variables that are particular to a given country.

Our study contributes to the existing literature by testing a large dataset of potential indicators from various sectors. In addition to hard data, we employ soft data, such as confidence indicators. The selected method, Bayesian model averaging (BMA) is capable of working with a large amount of data and identifying relationships between them. Second, we do not use the Basel gap, as recommended by the European Systemic Risk Board,[2] as it has certain limitations (which are discussed in further in Section 1) and thus it is not suitable for all countries. Based on this metrics, potential risks could be underestimated. For example, many European countries have experienced a large negative credit gap, yet the introduction of countercyclical capital buffers and macroprudential policy measures by policymakers has been observed as a reaction to rising risks within the financial system (Baba et al., 2020). Consequently, we adapt the credit-to-GDP gap in order to address the main critique. Third, given that the objective was to identify indicators

[2] Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates (ESRB/2014/1).

that affect the credit-to-GDP gap, the proposed approach may be of interest to regulatory authorities or policymakers, particularly when monitoring excessive credit growth or determining the level of the countercyclical capital buffer.

The structure of the rest of the paper is organized as follows. The first section provides an overview of the relevant studies on early warning indicators for a banking sector. The second section describes data and outlines the econometric approach. In the third section, the results are presented and the final section concludes.

1. Related Literature

In the literature, there exist various early warning systems that signal or measure potential problems in the banking system in different ways. There are models that attempt to predict a crisis event, identify rising financial imbalances or assess the current state of the banking sector. The objective of the majority of early warning systems is to identify a specific period within which the early warning system should highlight potential problems in the banking sector. Kaminsky and Reinhart (1999) set 12 months before or after a crisis as the maximum interval within which a signal of a potential crisis should be sent.

According to Drehmann and Juselius (2014), early warning indicators should send a signal at least 6 quarters before a crisis. Babecký et al. (2014) identify 2 horizons within which an early warning model should signal a crisis: short-term (5 – 8 quarters) and long-term (9 – 12 quarters).

In the case of signaling a potential crisis, the pioneering papers of Demirguc-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999) investigate the determinants of a banking crisis which could serve as early warning indicators for banking crisis. Using multinomial logistic regressions, Demirguc-Kunt and Detragiache (1998) suggest that the significant variables that increase the probability of a banking crisis include a decline in real GDP growth, a rise in inflation, a rise in the real interest rate, a decline in the exchange rate, a rise in the ratio of M2 to foreign exchange reserves, the existence of deposit insurance, and a "law and order" index that proxies for the effectiveness of law enforcement. A paper of Kaminsky and Reinhart (1999) which employs a signal approach posit that the best signals can be considered to be a decline in foreign exchange reserves, high real interest rates, low economic growth and falling stock prices.

The Basel Committee on Banking Supervision (2010) proposed the use of credit-to-GDP gap (Basel gap) to identify build-up of financial imbalances and as one of the main indicators when deciding on the implementation of a countercyclical capital buffer. This principle has also been incorporated in the EU's CRD IV (EU, 2019). The credit-to-GDP gap represents the principal reference indicator for the activation of the countercyclical capital buffer. However, other indicators to signal excessive credit growth can be used in addition. A number of papers (e.g., Borio and Lowe, 2002; Drehmann et al., 2011; Behn et al., 2013; Drehmann and Juselius, 2014; Detken et al., 2014 and Alessi and Detken, 2018) indicate that deviations of the credit-to-GDP ratio from its long-term trend could serve as a leading indicator of financial distress or instability and could signal an of increased probability of banking crisis. The aim of Alessi and Detken (2018) was to develop a model that would signal the build-up of financial imbalances and thereby identify the conditions under which banking sectors are exposed to crises. According to the authors, the random forest technique proves to be more accurate than regression models, as it takes into account non-linear relationships between indicators in determining early warning thresholds. The results indicate that, in addition to the credit-to-GDP gap indicator, it is necessary to consider different types of credit indicators, indicators related to the real estate market and global liquidity indicators.

However, a growing body of literature has pointed out shortcomings of the Basel gap which is advocated by the Basel Committee on Banking Supervision (BCBS) and European Systemic Risk Board. One of the main criticisms is the way it is calculated, in particular the use of the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) to estimate the long-run trend component[3] (Edge and Meisenzahl, 2011; Hamilton, 2018; Lang et al., 2019; Schüler, 2020). For example, Hamilton (2018) argues that the HP filter produces spurious dynamics that are not based on the underlying data and the data obtained in the middle and at the end of the sample are different. Repullo and Saurina (2011) claim that decision making on the countercyclical capital buffer based on a mechanical application of the Basel gap would lead to reduce capital requirements in bad times and vice versa. Other papers indicate that in certain countries the Basel gap underestimated risks during a period of excessive credit growth and reported negative credit gap (Castro et al., 2016; Lang and Welz, 2017; Lang et al., 2019, Baba et al., 2020). According to Geršl and Seidler (2012), the HP filter technique for calculation of the credit-to-GDP gap is not suitable for the Central and Eastern European countries, including Slovakia, as the rapid credit growth may be due to their convergence to advanced economies. In case of Slovakia, Rychtárik (2014) points outs several weaknesses of the Basel gap for the countercyclical capital buffer decisions but even it has limited signaling power, it can be used as a complement to guided judgment (Rychtárik, 2018).

[3] The long-term trend is based on a one-sided Hodrick-Prescott filter using a smoothing parameter (lambda) of 400‘000 on quarterly data, assuming that credit cycles are in the range 25 – 30 years (BCBS, 2010).

Another frequently used dependent variable of the early warning system is an excessive credit growth. Excessive credit growth has been identified by several authors as an indicator that can capture the disruption of financial stability and could be used as a predictor of the emergence of a banking crisis (Borio and Drehmann, 2009; Schularick and Taylor, 2012; Babecký et al., 2014; Geršl and Jašová, 2018).

The study of Babecký et al. (2014) is one of the first studies that use the BMA method in selecting early warning indicators for banking crises. They indicate that the optimal individual early warning indicator for different time horizons is private sector credit growth. In the 5 to 8 quarters preceding the crisis, the authors identified a number of additional indicators that were also found to be important: short-term money market interest rates, the increasing degree of openness of the economy, the rising share of industrial production in GDP, declining industrial production, a global indicator of the spread of Baa-rated U.S. corporate bonds, and a declining yield curve. In addition to private sector credit growth, the BMA identified two other important indicators for a banking crisis in the 9 to 12 quarters prior to the crisis: the increasing degree of openness of the economy and the declining spread of Baa-rated U.S. corporate bonds. Their results suggest that the best early warning indicators are related to investment optimism leading up to the boom phase of the economy and subsequent bust.

Within the Macroprudential Research Network initiated by the European System of Central Bank (2015) nine distinct early warning systems for banking crises were developed and compared. These prediction models were based on different approaches, including traditional probit and logit models, dynamic probit models, classification and regression tree approaches, and Bayesian econometric models. The proposed models included a variety of indicators related to credit, such as credit-to-GDP, credit growth, stock prices, housing prices, GDP, inflation, real effective exchange rate, short-term and long-term interest rate, debt service coverage ratio, current account, trade balance, government debt, capital flow, liquidity ratio, unemployment rate, or money supply. Multivariate approaches demonstrated superior early warning results compared to univariate signal models. Similarly, decision trees, such as the CART method and random forest, also demonstrated promising results. However, their out-of-sample prediction capabilities remain under-researched.

Other early warning systems, the so-called financial stress index, are designed to assess the health of the financial and banking sector (Illing and Liu, 2003; Hanschel and Monnin, 2005; Slingenberg and De Haan, 2011; Hakkio and Keeton, 2009; Vermeullen et al., 2015). The financial stress index summarizes the current situation in various sectors of the financial system, then presented in a single indicator at a given point in time. The index is designed to measure the level of financial stress, from a low state of stress to a period of high stress, when the financial sector is in crisis.

2. Data and Methodology

2.1. Data

We select a credit-to-GDP gap as our dependent variable which is supposed to give signals of emerging risks to banking sector. This indicator measures the deviation of the credit-to-GDP ratio from its long-run trend. The underlying assumption is that this indicator is indicative of excessive credit growth, which is related to the financial and business cycle nexus. The discrepancy between the credit-to-GDP ratio and its long-run trend suggests that household and corporate debt is growing at a faster rate than GDP, or new debt is no longer contributing sufficiently to GDP growth (Rychtárik, 2014). However, the application of the Basel gap metrics to the Slovak data yields negative credit gaps, despite the fact that during the period in question, the countercyclical capital buffers were in place and the National Bank of Slovakia implemented additional macroprudential measures with the objective to tightening credit standards (see Figure A1). Furthermore, Rychtárik (2014) illustrates that the Basel gap was weak to identify excessive credit growth during the period between 2005 and 2008 and generated a false noise in 2009. In light of these limitations of the Basel gap (as outlined in Section 1), we calculate the credit-to-GDP gaps based on the methodology proposed by Hamilton (2018) and Richter et al. (2021).

Firstly, we compute the credit-to-GDP as the ratio between the quarterly stock of domestic credit and nominal GDP summed over the four previous quarters, calculated based on the BCBS guidance (2010). To estimate the cyclical component, we adopt the approach of Hamilton (2018), who uses the residuals of a simple linear regression instead of the HP filtering.[4] Using quarterly time series, his approach assumes that the trend component of a variable at date $t+h$ can be predicted based on historical data. The cyclical component is defined as the difference between the observed value at date $t+h$ and the trend. Hamilton (2018) suggests a regression of the variable y at date $t+h$ on a constant and the $h = 4$ most recent values of y at date t:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h} \tag{1}$$

[4] We use the neverhpfilter package of Shea (2022) to estimate the cyclical component of the credit-to-GDP.

which can be written as:

$$y_t = \beta_0 + \beta_1 y_{t-h} + \beta_2 y_{t-h-1} + \beta_3 y_{t-h-2} + \beta_4 y_{t-h-3} + v_t \tag{2}$$

The h denotes a horizon, which is the length of the cyclical component in terms of the number of h periods (quarters). Hamilton (2018) recommends a horizon of $h = 4$ for quarterly macroeconomic and financial time series and a longer horizon $h = 20$ for debt cycles. We choose a horizon $h = 12$ (quarter) based on Richter et al. (2021) who identify credit boom by applying the Hamilton detrending approach with a horizon of 3 years on annual panel dataset for 17 countries over almost 150 years.

In selecting the independent variables or potential early warning indicators, we consider the existing theory and empirical evidence on early warning systems for the banking sector. The dataset includes a number of "traditional" indicators, which are compiled with a time lag. In addition, we gather indicators that should signal problems with a shorter time lag, in particular, we use market data and confidence indicators. In this study, we use 38 potential early warning indicators (see a detailed list of variables with respective category in Table A1) which we divide into following categories:

- Macroeconomic indicators.
- Monetary indicators.
- Bank-related indicators.
- Fiscal indicators.
- Confidence indicators.
- External indicators.
- Financial market indicators.

Early warning indicators should reflect the different risks that banks may face. Banks are exposed to a multitude of risks in the course of their operations. The risks to which banks are exposed include: interest rate risk, credit risk, market risk, liquidity risk, operational risk, systemic risk, sovereign risk and contagion risk. Furthermore, the choice of indicators should take into account the specific characteristics the banking sector in a given country.

Macroeconomic variables are supposed to identify macroeconomic imbalances that may represent a risk factor for financial institutions. Early warning macroeconomic indicators that have been identified in the literature include GDP growth, the output gap, GDP per capita, industrial production, unemployment, exchange rate depreciation, investment, the ratio of net national savings to gross national income or gross fixed capital formation. Furthermore, the banking sector may also be affected by household financial conditions, such as household final consumption expenditure, total household financial assets household net income.

With regard to monetary indicators, the following indicators can be found in the literature: the interest rate, the monetary aggregates M1 and M3, inflation. The banking sector-specific indicators are based on banks' balance sheets and profit and loss accounts. These data should capture the health of the banking sector. The structure of liabilities on a bank's balance sheet can provide information on the liquidity risk of a given bank. The source of difficulties in the banking sector may also be found on the asset side. The indicators used in monitoring the banking sector include ratio of banks' cash and reserves to total bank assets, deposits, non-performing loans, net interest spread, return on equity, return on assets.

Among the fiscal indicators used in predicting banking crises, the following indicators have been used: government debt-to-GDP ratio, government budget deficit-to-GDP, tax burden (as a share of GDP), or government consumption.

Confidence indicators should provide the most recent information on the assessment of current developments and the expectations of economic agents about the future development of the economic environment and its individual industries and sectors. Their advantage is the speed and timeliness of the data obtained. Furthermore, business and consumer surveys could indicate future excessive credit growth in the economy (Rychtárik, 2018).

External indicators also appear in papers on early warning systems, which aim to capture the external element or international position that some authors have argued was an important factor in banking crises. The following external indicators have been identified in the literature as increasing the vulnerability of the banking sector: the current account to GDP ratio, trade balance, foreign capital flows, foreign debt, foreign reserves to GDP ratio, global GDP growth, OECD GDP growth, interest rates in the US and Germany, and the price of oil. Some studies tried to predict crises using financial market data, for example, by using different types of spreads,[5] the 10-year Treasury bond, or the evolution of stock prices. In this category, indices that aim to capture uncertainty in the financial market may also be included, such as the VIX volatility index or the Policy Uncertainty Index.

The data were collected on a quarterly basis for the period from the first quarter of 2003 to the last quarter of 2023.[6] Table 1 provides descriptive statistics of all variables. We test for the presence of unit roots using the KPSS test as suggested by Sul et al. (2005)[7] and check collinearity between explanatory variables.[8]

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[5] For example, spread between domestic long-term interest rate and the US long-term interest rate, difference between the long-term and the short-term rate.

[6] However, not all indicators were available as of 1Q2003. Nevertheless, we decided to include them in the analysis as we assume that these indicators may be important for the credit-to-GDP gap.

[7] We either take percentages or take the differences if the null hypothesis of a unit root is rejected.

[8] If the Pearson's correlation coefficient was above 0.80, one of the explanatory variables with a lower correlation with the dependent variable was removed.

T a b l e 1
Descriptive Statistics

	Variable	Format	Mean	SD	Min	Max
B10	Credit-to-GDP gap	%	0.13	3.06	–9.19	5.17
B5	Loans to households of total financial assets	%	38.62	9.20	14.61	51.08
B12	Return on assets	%	0.59	0.30	0.08	1.27
B6	Loans to household (% of GDP)	%	30.39	11.91	7.81	47.09
E2	Net external debt (% of GDP)	%	22.17	9.98	–7.00	33.9
E3	Current account balance	%	–3.79	4.69	–17.7	5.20
E4	GDP growth Germany	%	0.29	1.69	–9.20	8.90
E5	GDP growth EU	%	0.33	1.88	–10.9	11.30
E6	Direct investment	mil. EUR	–319.68	639.57	–1821.63	1679.24
E7	Portfolio investments	mil. EUR	6.93	1321.69	–3464.9	2273.3
E8	EU Policy uncertainty index	Index	188.2	83.45	60.85	433.28
E9	GER Policy uncertainty index	Index	212.15	169.79	40.67	844.85
FM1	10Y German govt bond yield	%	1.93	1.64	–0.58	4.58
FM2	10Y Slovak govt bond yield	%	2.80	1.89	–0.52	5.42
FM4	DAX index	Index	8933.95	3696.58	2491.05	16041.18
FM10	Index of financial stress	Index	0.10	0.07	0.03	0.40
F2	Government debt (% of GDP)	%	46.53	9.87	26.60	60.20
F3	Budget deficit / surplus (% of GDP)	%	–3.32	2.51	–11.70	1.80
D2	Industrial confidence indicator	Index	1.06	7.99	–31.40	15.10
D3	Construction confidence indicator	Index	–21.96	16.91	–57.20	2.80
D4	Retail confidence indicator	Index	12.63	11.24	–21.60	35.60
D5	Services confidence indicator	Index	16.20	18.78	–43.90	57.80
C16	Consumer confidence indicator	Index	–18.15	9.68	–37.70	2.60
R1	Unemployment rate	%	11.20	3.95	5.70	19.00
R2	Average wage	EUR	864.35	242.40	457.78	1440.68
R3	GDP growth	%	0.84	2.09	–9.70	9.70
R5	Index of industrial production	Index	88.95	21.30	50.10	120.60
R6	Private consumption of households	EUR	11468	1831	7949	14737
R8	Total financial assets of households	EUR	60482	25491	22736	106402
M3	IR on outstanding loans to households	%	5.82	2.42	1.61	9.92
M4	IR on outstanding loans to NFC	%	3.42	1.67	1.68	7.72
M7	IR on outstanding housing loans to households	%	3.88	2.06	0.94	7.63
M9	HICP	Index	98.04	14.02	72.92	139.20
M10	HICP – Housing, water, electricity, gas, other fuels	Index	95.19	15.09	58.94	132.20
M12	House Price Index	Index	38.03	12.51	20.68	72.97
M13	IR on new loans to households	%	6.14	2.91	1.51	11.20
M14	IR on new loans to NFC	%	3.40	1.67	1.63	7.39

Notes: IR stands for interest rate, HICP stands for Harmonized Index of Consumer Prices, NFC denotes non-financial corporations.

Source: Own calculations based on data sources provided in Table A1.

One of the main challenges of the early warning systems is related to selecting an optimal prediction horizon. The early warning indicators should have the ability to warn of potential problems well in advance, so that policy makers have enough time to take measures. On the other hand, indicators should not issue warnings of a crisis too early, as too early implementation of measures entails additional costs. In addition, indicators should also be straightforward to interpret (Drehmann and Juselius, 2014). Considering the time needed for decision-making and setting up countercyclical capital buffer measures (usual to 12-month implementation phase[9]), we combine time horizons proposed by Alessi and Detken (2011), Behn et al. (2013), Drehmann and Juselius (2014), Babecký et al. (2014), Geršl and Jašová (2018) and Filippopoulou et al. (2020). More specifically, we look at different warning horizons from one year up to three years (horizon from 4 to 12 quarters). This should give policy makers time to take appropriate measures and furthermore, the use of a time lag should help to overcome the endogeneity problem.

2.2. Methodology

Given the uncertainty involved in choosing appropriate indicators and combinations of indicators in the model, we used Bayesian Model Averaging (BMA) to identify early warning indicators that could explain changes in the dependent variable, in our case the credit-to-GDP gap. We estimate following linear regression model:

$$y_t = \alpha^i + X^i_{t-l}\beta^i + \varepsilon^i_t \varepsilon^i_t N\left(O,\sigma^{2,i}\right)\frac{1}{2} \tag{3}$$

where

y_t – the credit-to-GDP gap,
α_i – a constant,
X^i_{t-1} – a $1 \times k_i$ vector of explanatory variables (early warning indicators),
k – a number of explanatory variables,
β_i – a vector of coefficients,
ε^i_t – the residuals with a normal distribution and variance $\sigma^{2,i}$,
$t = 1, 2, \dots T$ denotes the time index (quarter),
$l = 4, 5, \dots 12$ denotes number of lags.

The BMA takes into account the different combinations of indicators in the models and weights them according to how they fit into the model. Each model M^i contains a specific combination of explanatory variables (early warning indicators) for which $i = 1, 2, \dots, 2^K$, in the number of potential explanatory variables is denoted by K, and the number of all combinations of explanatory variables is given by $J = 2^K$. In addition to selecting indicators, BMA also allows us to show how important each explanatory variable is for the credit-to-GDP gap. The importance or weight of explanatory variables in BMA is given by the posterior inclusion probability (PIP), which is the sum of the posterior probabilities of all the models that contain the indicator. The PIP is defined as follows for a coefficient β_h and for a given D (our data):

[9] Under CRD IV, banks are given 12 months to apply the countercyclical buffer rate but the implementation phase could be shortened. Rychtárik (2018) suggests that gap between the announcement date and the deadline is usually close 6 quarters.

$$P\left({}_{h}|D \right) = \sum\nolimits_{j=1}^{J} P\left({}_{h}|M^{j} \right) P\left(M^{i}|D \right) \tag{4}$$

where

$P\left(M^{i}|D \right)$ is the posterior model probability which is used as a weight by the BMA.

The PIP indicates the probability of a variable being included in the correct model, or how important each variable is for the variable being explained. The PIP value can range from 0 to 1 (or 0% to 100%). The higher the PIP value, the more important the variable is for the dependent variable. In the literature, there is no unified view on the threshold value of PIP from which a variable can be considered important. According to Barbieri and Berger (2004), variables with a PIP greater than 0.5 are deemed to have optimal predictive ability. Kass and Raftery (1995) proposed four categories for indicating importance of predictors: a weak impact (PIP of 0.5 – 0.75), a substantial impact (PIP of 0.75 – 0.95), a strong impact (PIP of 0.95 – 0.99) and a decisive impact (PIP greater than 0.99). In assessing the indicators in question, we combine both assessment approaches: following the approach of Barbieri and Berger (2004) and Feldkircher (2012) in selecting variables with a PIP greater than 0.5 and focusing on indicators with at least substantial impact at any horizons.

We perform Bayesian model sampling with the R package BMS of Feldkircher et al. (2022). We specify priors for parameters (hyperparameter "Zellner g-prior") and model based on Eicher et al. (2011) and Babecký et al. (2014). The hyperparameter determines the choice of the a priori density of the coefficients, which is based on the researcher's opinion. The hyperparameter g reflects the researcher's prior assumptions about the distribution of the coefficients. A lower g means that the researcher is conservative and less certain that the variables will be significant for the dependent variable. On the other hand, a higher g indicates that the researcher is not sure that the coefficients are equal to zero. We employ the uniform model prior (UIP). The UIP g-prior sets g = N for all models, where N is the number of observations. The UIP assumes that we have no prior information about the distribution of the coefficients. We set a uniform prior probability for all models that should represents the lack of prior knowledge. With 2^{K} potential models to consider,[10] the BMS package implements MCMC (Markov Chain Monte Carlo) samplers to approximate the most important part of the posterior model distribution (PMP). We rely on the reversible-jumper sample proposed by Madigan and York (1995). As the MCMC algorithm removes the first set of iterations from the computation, we follow Feldkircher et al. (2014) by discarding 1'000'000 burn-in iterations and subsequently we retain 3'000'000 iterations of the MCMC sampler for convergence.

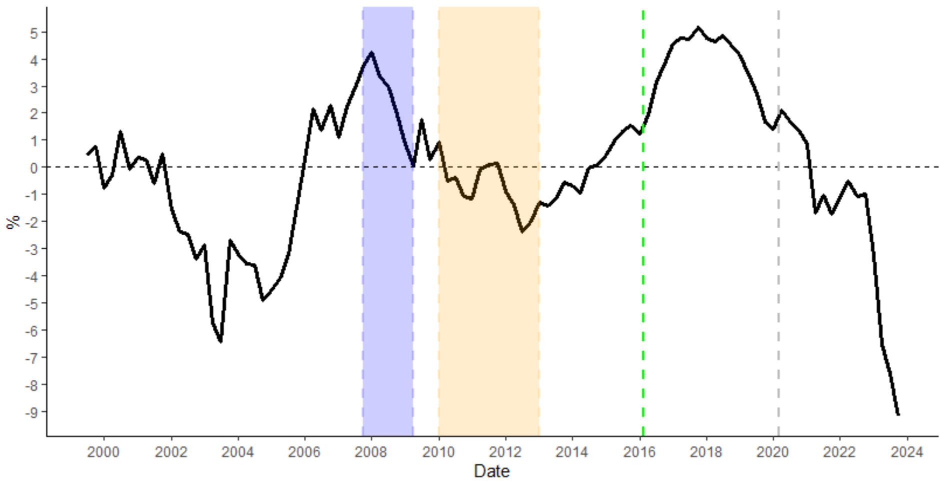
[10] The full model space is 2^{35} in our case, after removing correlated variables.

For a robustness check, we replicated our analysis using alternative assumptions of g prior and model priors. Following Feldkircher and Zeugner (2009) and Ley and Steel (2012), we choose the hyper-g prior as defined in Liang et al. (2008). This hyperparameter lets the data decide and adjusts the weight of prior knowledge according to the quality of the data. Then, we employ the binomial-beta random prior of Ley and Steel (2009) as we do not prefer a specific model size.

3. Findings and Discussion

Figure 1 illustrates the development of the credit-to-GDP gap. Prior to the global financial crisis (purple area), there were indications of growing risks to financial stability for the Slovak financial sector, as evidenced by an increase in the credit-to-GDP gap in 2009. The Slovak banking sector experienced difficulties; however, the overall financial stability was not threatened, with the financial system absorbing the risks. In the period preceding the sovereign debt crisis in the euro area (orange area), the credit gap was positive but less than 2%, which is a suggested threshold for the activation of the countercyclical capital buffer (BCSB, 2010). The Slovak banking sector demonstrated resilience during the crisis period.

Figure 1
Credit-to-GDP Gap in Slovakia



Notes: The purple shaded area represents the global financial crisis, the orange shaded area the eurozone sovereign crisis, the green vertical line shows the implementation of a law that reduced the maximum fee charged by banks for early loan repayments, and the grey vertical line indicates the start of the first declaration of a state of emergency due to the Covid-19 pandemic.

Source: Based on data provided by the National Banks of Slovakia and Eurostat.

Afterwards, the credit-to-GDP gap exhibited upward trajectory. The household indebtedness emerged as a significant concern, prompting the National Bank of Slovakia to implement a series of macroprudential measures with the potential to contribute to a reduction in the credit gap. After the onset of the Covid-19 pandemic, a decline in the credit-to-GDP gap can be observed. Despite mounting pressure on financial stability, the position of banks has remained robust.

In Table 2 we report indicators with respective category that have a PIP above 0.5 for each prediction horizon. The PIP shows a probability that a variable is included in the best 2000 models with the highest PMP during iteration. Further variables statistics, including posterior mean (PM), posterior standard deviation (PSD) and conditional positive sign (CPS), are indicated in Table A2.[11] In addition, the result Table 2 shows model diagnostics, including the average number of included regressors (posterior expected model size), the "Bayesian goodness-of-fit" indicator (Shrinkage factor)[12] and the convergence rate between the analytical and MCMC PMPs for the "top" 2000 models (Corr PMP). Across all prediction horizons, the correlation between the analytical likelihoods and iteration counts suggests a good sign of convergence of the MCMC sampler and the values under the shrinkage factor are close to 1 indicating a relatively good fit. Using alternative prior setup as a robustness check, the results are pretty much consistent across time horizons.

The BMA analysis shows two interesting findings. First, the confidence and external indicators seem to be important across multiple warning horizons. Second, besides traditional hard data, soft data collected through surveys and questionnaires could have a signaling ability. At a shorter horizon of between 4 and 6 quarters, the Policy Uncertainty Index[13] which measures uncertainty based on the newspaper articles related to policy uncertainty in Germany seems to be an important early warning indicator. The importance of this indicator suggests that the Germany's economy is also important for the Slovak banking sector. The current account balance (as a percentage of GDP) also seems to be also important indicator for the banking sector. Giese et al. (2014) and Plašil et al. (2015) show that current account deficits can send signals of increasing vulnerability, especially in small open economies. This indicator is also incorporated in two measures designed by the National Bank of Slovakia: the "cyclogram" (Rychtárik, 2018) and the financial cycle indicator (Kupkovič and Šuster, 2020). These tools are designed to assist with the monitoring of the build-up phase of risks.

[11] PM shows coefficients averaged across all modes, PS denotes coefficients' posterior standard deviations and CPS indicates the posterior probability of a positive sign conditional on inclusion.

[12] Shrinkage factor of values close to 1 indicates a good fit (Zeugner and Feldkircher, 2015).

[13] Created by Baker et al. (2016), this index is considered to be an indicator of uncertainty associated with various policy measures such as monetary policy measures, fiscal policy, and other regulations at the country level.

T a b l e 2

Posterior Inclusion Probabilities of Top Variables

		4Q	**5Q**	**6Q**	**7Q**	**8Q**	**9Q**	**10Q**	**11Q**	**12Q**
Variable	*Category*	PIP	PIP	PIP	PIP	PIP	PIP	PIP	PIP	PIP
Loans to HH (% of GDP)	Bank-related	0.97	0.78	0.79	0.99	1.00	1.00	1.00	0.70	
HICP	Monetary		0.89	0.93	0.63	0.89	0.78	0.60		
HICP – housing, water, electricity, gas, other fuels	Monetary					0.86	0.72	0.60		
IR on housing loans to HH (outstanding amount)	Monetary	0.95	0.85							
IR on new loans to NFC	Monetary	0.81								
GER Policy uncertainty index	External	0.65	0.98	0.98	0.97	0.83				
Covid-19	External						0.62	1.00	1.00	1.00
Current account balance	External				0.53	0.81	0.53	0.95	0.83	0.84
GDP growth	Macroeconomic	0.52								
Unemployment rate	Macroeconomic	0.54	0.51	0.61	0.67	0.56	0.67			0.63
Construction confidence index	Confidence	0.50	0.93	0.81	0.60	0.73		0.68		
Consumer confidence index	Confidence	0.94								
Index of financial stress	Financial markets							0.50		
Model size		10.38	10.51	10.23	9.43	11.00	9.99	10.44	9.31	9.32
Shrinkage		0.986	0.986	0.985	0.985	0.985	0.985	0.984	0.984	0.984
Corr PMP		0.984	0.974	0.977	0.984	0.986	0.967	0.979	0.963	0.959

Notes: PIP denotes posterior inclusion probability, HH stands for households, NFC stands for non-financial corporation, IR stands for interest rate, and HICP stands for Harmonized Index of Consumer Prices.

Source: Own calculations.

In the long run, the Covid-19 pandemic seems to be an important factor for the banking sector, which contributed to the increase of systemic risks and higher credit risks within the Slovak banking sector. This is consistent with recent research on the impact of Covid-19 pandemic on the banking sector, for example, on the equity prices of European banks (Borri and Di Giorgio, 2022), the systemic stability of the banking system (Duan et al., 2021), bank performance and financial stability (Elnahas et al., 2021; Shabir et al., 2023) or on credit growth (Çolak and Öztekin, 2021).

Sentiment based on business and consumer survey could be also relevant in signaling growing problems in the Slovak banking sector. This is in line with Rychtárik (2018) who proposed a "cyclogram" comprising an aggregated economic sentiment indicator and other indicators, with the objective of assisting in deciding on countercyclical capital buffer rate. The construction confidence indicator seems to be important for multiple warning horizons with a positive average coefficient. This composite indicator evaluates the current situation of construction companies and also reflect their expectations for the next three months. This confidence indicator not only captures an assessment of the current situation, but also reflects expectations for future developments in both output and the number of employees. The construction industry is considered to be one of the important sectors in the Slovak economy. The development of construction output is also an important indicator of the development of the Slovak economy (Ministry of transport and construction of the Slovak Republic, 2019). The positive effect on the credit-to-GDP gap can be interpreted as positive expected developments in the construction sector leading to a construction boom, mainly supported by excessive lending, which can lead to growing imbalances in the banking sector.

Indebtedness of the Slovak households measured by household debt-to-GDP ratio seems to be also an important early warning indicator across all horizons. This is in line with a study of Drehmann and Juselius (2012) and Alessi and Detken (2018) that suggest that an increase in the share of household debt to GDP is associated with a higher probability of a banking crisis. Indebtedness of Slovak households has grown rapidly during the last two decades; even during the global financial crisis we recorded its growth, although the pace was slower. Our results indicate that the growth of household debt leads to an increase in the credit-to-GDP gap and thus to the accumulation of risks in the Slovak banking sector. The importance of this indicator is confirmed by measures taken by the National Bank of Slovakia, which aim to reduce the excessive growth of indebtedness of Slovak households.

The BMA results confirm that it is also important to monitor "traditional" indicators such as the unemployment rate, inflation, and the interest rate. The importance of unemployment rate for the banking sector is in line with multiple studies that associate an elevated unemployment rate with heightened risks in the banking sector (e.g., Berge and Boye, 2007; Nkusu, 2011; Louzis et al., 2012; Chaibi and Ftiti, 2015). The unemployment rate is also part of "cyclogram" developed by the National Bank of Slovakia (Rychtárik, 2018). Among the "traditional" monetary indicators, the interest rate on housing loans (outstanding amount) provided to households and on new loans granted to non-financial corporations, the inflation measured by Harmonised Index of Consumer Prices (HICP) and HICP for housing, water, electricity, gas and other fuels seem to be have a signaling power. Inflation has been identified as a robust early warning indicator by many authors: Dermiguc-Kunt and Detragiache (1998), Hardy and Pazarbasioglu (1999), Cashin and Duttagupta (2011) and Ristolainen (2018). As anticipated, the interest rates have an expected negative sign, as a declining interest rate environment contributes to the build-up phase and could potentially lead to boom-bust episodes (Elekdag and Wu, 2013). The role of interest rates as an early warning indicator for banking issues is supported by evidence presented in the existing literature (Von Hagen and Ho, 2007; Davis et al., 2011). Additionally, the interest rate on loans to households and non-financial corporations serve as an input indicator for financial cycle identification for Slovakia (Kupkovič and Šuster, 2020).

Conclusion

In this paper, we tried to identify early warning indicators for the Slovak banking sector. The goal of early warning indicators is to signal rising risks or imbalances in the banking sector as a whole. We tested a power of 38 potential variables from different sectors in predicting rising risks in the banking sector for a warning horizon from 4 up to 12 quarters. We chose the credit-to-GDP gap, estimated based on an approach of Hamilton (2018) to account for issues related to HP filtering, as a proxy for capturing growing financial imbalances and the accumulation of risks in the banking sector. We used the Bayesian Model Averaging (BMA) method to identify for significant potential early warning indicators. This method accounts for uncertainty when deciding on the selection and combination of potential indicators in the early warning system. The BMA method can test a large number of indicators, including potentially insignificant variables, without impacting the result.

Based on the BMA analysis, we found out that along "traditional" early warning indicators such as the unemployment inflation, inflation or interest rates, it is worth monitoring indicators that try to reflect uncertainty. In our case, uncertainty is captured by sentiment-based survey indicators and newspaper articles related to policy uncertainty. More specifically, the confidence indicator for the construction sector and Policy uncertainty index for Germany appear to be important for the development of the Slovak banking sector. Furthermore, the Slovak banking sector is susceptible to external shock such as a Covid-19 pandemic. Additionally, the current account balance is an important factor to consider, given the Slovakia's position as a small open economy. Moreover, our findings suggest that the household debt as a percentage of GDP may send a signal of emerging imbalances in the banking sector.

Given that we try to identify the drivers of the credit-to-GDP gap for prediction horizons ranging from 1 year to 3 years, the results and approach can be deemed relevant in the context of macroprudential policy, particularly when deciding on the level of the countercyclical capital buffer. Some of the identified indicators, for example the current account balance, confidence indicators, unemployment rate and interest rates, are also part of analytical tools, namely the cyclogram and the financial cycle indicator, developed by the National Bank of Slovakia. However, as emphasized by the guidance from both the BSBS (2010) and the ESRB (2018), as well as numerous research papers (e.g., Bonfi and Monteiro, 2013; Giese et al., 2014; Jokipii et al., 2021), in addition to the credit-to-GDP gap, policymakers at the national level should consider further indicators to monitor potential risks to financial stability and determining the size of capital buffers or adopting a macroprudential stance.

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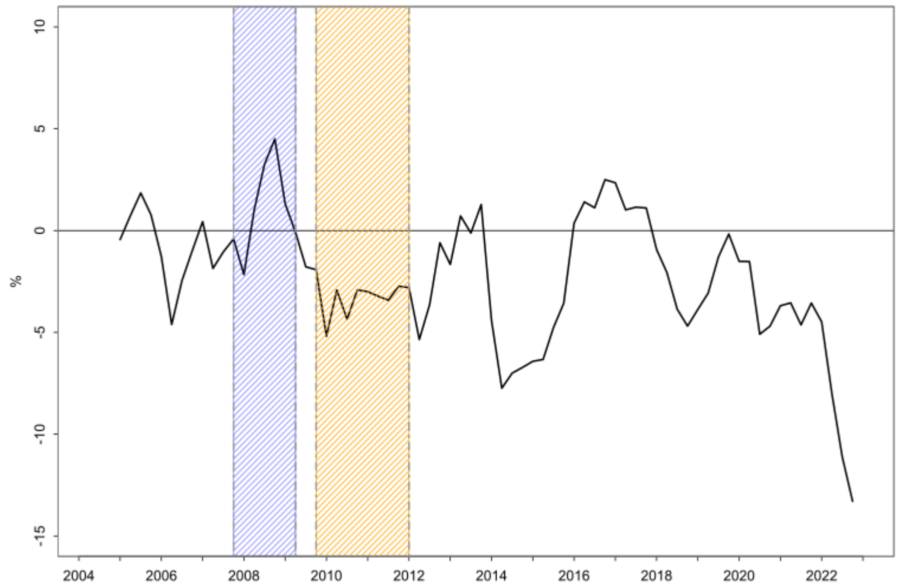
Appendix

Figure A1

Basel Credit-to-GDP Gap in Slovakia



Notes: The blue shaded area represents the global financial crisis and the orange shaded area represents Eurozone sovereign crisis.

Source: Based on data provided by the ECB.

Table A1

Description of Variables

	Variable	Source	Category	Notes
B10	Credit-to-GDP gap	NBS/Eurostat		
B5	Loans to households as % of total financial assets	ECB	Bank-related	
B6	Loans to household as % of GDP	ECB	Bank-related	
B12	Return on assets	NBS	Bank-related	
E2	Net external debt (as % of GDP)	Eurostat	External	Neither seasonally adjusted nor calendar adjusted, net liabilities
E3	Current account balance	NBS	External	As a percentage of GDP
E4	GDP growth Germany	Eurostat	External	Chain linked volumes, seasonally and calendar adjusted
E5	GDP growth EU	Eurostat	External	Chain linked volumes, seasonally and calendar adjusted
E6	Direct investments	NBS	External	Balance, not seasonally adjusted, international investment position

E7	Portfolio investments	NBS	External	Balance, not seasonally adjusted, international investment position
E8	EU Policy uncertainty index	policyuncertainty.com	External	
E9	GER Policy uncertainty index	policyuncertainty.com	External	
FM1	10Y German govt bond yield	Stooq	Financial markets	
FM2	10Y Slovak govt bond yield	OECD	Financial markets	
FM4	DAX index	Stooq	Financial markets	
FM10	Index of financial stress for Slovakia	ECB	Financial markets	
F2	Government debt (% of GDP	Eurostat	Fiscal	Government consolidated gross debt
F3	Budget deficit / surplus (% of GDP)	Eurostat	Fiscal	Seasonally and calendar adjusted data
D2	Industrial confidence indicator	Eurostat	Confidence	Seasonally adjusted
D3	Construction confidence indicator	Eurostat	Confidence	Seasonally adjusted
D4	Retail confidence indicator	Eurostat	Confidence	Seasonally adjusted
D5	Services Confidence Indicator	Eurostat	Confidence	Seasonally adjusted
C16	Consumer Confidence Indicator	Eurostat	Confidence	Seasonally adjusted
R1	Unemployment rate	Eurostat	Macroeconomic	Seasonally adjusted
R2	Average wage	NBS	Macroeconomic	Seasonally adjusted
R3	GDP growth	Eurostat	Macroeconomic	Chain linked volumes, seasonally and calendar adjusted
R5	Index of industrial production	Eurostat	Macroeconomic	Seasonally adjusted, 2015 = 100
R6	Private consumption of households	NBS	Macroeconomic	Final consumption expenditure, seasonally adjusted, constant prices
M3	IR on outstanding loans to households	NBS	Monetary	
M4	IR on outstanding loans to NFC	NBS	Monetary	
M7	IR on outstanding housing loans	NBS	Monetary	Households
M9	HICP	NBS	Monetary	Not seasonally adjusted
M10	HICP – Housing, water, electricity, gas and other fuels	NBS	Monetary	Not seasonally adjusted
M12	House Price Index	ECB/NBS	Monetary	2015 = 100
M13	IR on new loans to households	NBS	Monetary	
M14	IR on new loans to NFC	NBS	Monetary	
D1	Eurozone crisis	Literature	Macroeconomic	Sovereign debt crisis
D6	Covid-19 crisis	health.gov.sk	External	Official declarations of state of emergency

Note: ECB stands for European Central Bank, NBS stands for National Bank of Slovakia, NFC stands for non-financial corporations.

Source: Created by the authors.

T a b l e A2

BMA Estimates

	4Q			**5Q**			**6Q**		
Variable	PM	PSD	CPS	PM	PSD	CPS	PM	PSD	CPS
B6	1.770	0.616	1.000	1.181	0.827	1.000	1.527	1.046	1.000
M9				–0.742	0.372	0.000	–1.090	0.514	0.000
M7	–0.072	0.028	0.000	–0.055	0.033	0.000			
M14	–0.032	0.021	0.000						
E9	–0.002	0.002	0.000	–0.006	0.002	0.000	–0.008	0.002	0.000
R3	–0.139	0.174	0.001						
R1	–0.053	0.060	0.000	–0.049	0.060	0.000	–0.084	0.082	0.000
D3	0.022	0.027	0.997	0.068	0.027	1.000	0.055	0.034	1.000
C16	0.140	0.056	1.000						
	7Q			**8Q**			**9Q**		
	PM	PSD	CPS	PM	PSD	CPS	PM	PSD	CPS
B6	3.150	0.970	1.000	3.886	0.956	1.000	4.281	1.002	1.000
M9	–0.598	0.597	0.000	–1.684	0.852	0.000	–1.516	1.048	0.000
M10				0.553	0.298	1.000	0.463	0.362	1.000
E9	–0.009	0.003	0.000	–0.007	0.004	0.000			
D6							–1.757	1.699	0.000
E3	0.078	0.091	1.000	0.179	0.112	1.000	0.094	0.111	1.000
R1	–0.105	0.093	0.000	–0.088	0.097	0.000	–0.127	0.110	0.000
D3	0.032	0.032	1.000	0.044	0.034	1.000	0.017	0.027	1.000
B6	3.150	0.970	1.000	3.886	0.956	1.000	4.281	1.002	1.000
M9	–0.598	0.597	0.000	–1.684	0.852	0.000	–1.516	1.048	0.000
M10				0.553	0.298	1.000	0.463	0.362	1.000
	10Q			**11Q**			**12Q**		
	PM	PSD	CPS	PM	PSD	CPS	PM	PSD	CPS
B6	3.886	0.934	1.000	1.684	1.393	1.000			
M9	–0.833	0.841	0.000						
M10	0.358	0.326	1.000						
D6	–5.273	1.189	0.000	–6.617	1.282	0.000	–7.213	1.289	0.000
E3	0.235	0.093	1.000	0.169	0.105	1.000	0.167	0.099	1.000
R1							–0.104	0.099	0.000
D3	0.037	0.032	1.000						
FM10	4.035	4.929	1.000						

Notes: PM denotes posterior mean, PSD denotes posterior standard deviation, CPS denotes conditional positive sign (CPS).

Source: Authors' calculation.