frontiers
in Applied Mathematics
and Statistics

TYPE Original Research
PUBLISHED 05 November 2026
DOI 10.3389/fams.2026.1974941

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OPEN ACCESS

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RECEIVED 21 August 2026
REVISED 22 October 2026
ACCEPTED 22 October 2026
PUBLISHED 05 November 2026

CITATION
Pavlenko O and Fjodorovs J (2026) Modelling and forecasting recessions with classical and regime-dependent logistic models: evidence from Latvia. *Front. Appl. Math. Stat.* 12:1974941. doi: 10.3389/fams.2026.1974941

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Modelling and forecasting recessions with classical and regime-dependent logistic models: evidence from Latvia

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Recession forecasting is important for economic policy, financial risk management, and business planning. This study examines recession modelling and forecasting using publicly available quarterly Latvian macroeconomic data. Three logistic specifications are developed and compared: classical logit, threshold logit, and smooth transition logistic models. The nonlinear specifications allow the effects of key recession predictors to vary across economic regimes. Predictors are selected using correlation analysis and multicollinearity diagnostics, based on which inflation, manufacturing confidence, and lagged recession dynamics are chosen. We assess model performance using in-sample fit measures, including information criteria and McFadden's pseudo-R^2, and out-of-sample forecast accuracy using the Brier score and mean absolute error. The models are also compared using the area under the receiver operating characteristic (ROC) curve (AUC). The results indicate that regime-dependent models provide stronger in-sample fit than the classical specification. In the out-of-sample evaluation, the smooth transition logistic model records the lowest Brier score and mean absolute error among the three models. The results provide empirical evidence that regime-dependent logistic specifications can be useful for modelling recession probabilities in small open economies like Latvia, although the limited number of observations, imbalanced data, and only 18-step-ahead forecast calls for cautious interpretation of the forecasting results.

KEYWORDS
forecast accuracy, logistic regression, recession, smooth transition model, threshold model

1 Introduction

Forecasting macroeconomic recessions is important for governments, financial institutions, and businesses wishing to make correct decisions accounting for recession risks. It is particularly relevant for small open economies such as Latvia, where economic fluctuations may depend not only on domestic developments but also on external shocks, changes in prices, and financial conditions. In such an environment, the relationship between macroeconomic indicators and recession risk may not remain constant throughout the business cycle. This motivates models that include the effects of explanatory variables dependent on economic regimes.

Threshold models provide one of the principal approaches for representing such regime dependence. Tong (1) established threshold models for nonlinear time-series analysis, in which

the dynamics of a process may change when a transition variable crosses a threshold. A threshold specification therefore represents a discrete change between regimes and can be particularly useful when economic relationships are expected to differ between relatively weak and strong economic conditions. Aydin and Mermi (2) considered alternative regime-switching and regime-dependent approaches for economic time series, further demonstrating the importance of regime-dependent structures in economic modelling. More recent research has also examined threshold effects directly in regression models. Lee et al. (3), for example, provide a formal framework for testing threshold effects in regression models, supporting the use of threshold specifications when the relationship between explanatory variables and an economic outcome may change after a transition variable reaches a particular level.

Smooth-transition models offer a related but more flexible approach to regime dependence. Rather than imposing an abrupt change at a single threshold, smooth-transition models allow the coefficients to change gradually as a transition variable moves between regimes. Teräsvirta and Anderson (4) developed the smooth-transition autoregressive model for describing nonlinearities in business-cycle dynamics, while Teräsvirta (5) provided a general framework for the specification, estimation, and evaluation of smooth-transition autoregressive models. This approach is particularly relevant when economic adjustment is expected to occur progressively rather than through an immediate switch from one regime to another. Hurn et al. (6) demonstrate the application of a smooth-transition logistic model to an economic policy problem, illustrating how smooth-transition mechanisms can also be incorporated into binary-response models.

Nonlinear modelling is also relevant in the Latvian empirical literature. Pavlenko and Matvejevs (7) compared linear and nonlinear models for forecasting food commodity prices in Latvia, providing evidence that nonlinear specifications can be useful for Latvian economic data. Pavlenko (8) considered asymmetric-transition time-series models for Latvian economic indicators. Pavlenko and Zeltina (9) applied a second-order logistic smooth-transition autoregressive model to the Latvian unemployment rate, demonstrating the applicability of smooth-transition structures to Latvian labour-market dynamics. Pavlenko (10) further investigated smooth-transition autoregressive models for the Latvian unemployment rate. These studies indicate that nonlinear and regime-dependent models can be relevant for Latvian macroeconomic time series. Recent Latvian research also demonstrates the application of logistic regression to empirical modelling of binary outcomes. Budkuna et al. (11) investigated the determinants of degree completion in Financial Engineering at Riga Technical University using a logit model. Although that study concerns an educational rather than a macroeconomic outcome, it provides additional context for the application of interpretable binary-response models in Latvian empirical research. Logistic regression is appropriate for recession forecasting because it directly estimates the probability of a recession conditional on a set of explanatory macroeconomic variables.

Recent international research provides a broader context for the use of logistic and other binary-response models in recession forecasting. Estrella and Mishkin (12) examined financial and macroeconomic variables for U.S. recessions using out-of-sample forecasts at horizons ranging from one to eight quarters, demonstrating the usefulness of financial and leading economic indicators for recession prediction. Their study provides an important foundation for recession-probability models in which macroeconomic and financial variables are used to estimate the probability of a future recession. Kauppi and Saikkonen (13) extended the binary-response approach by developing dynamic probit models that explain the persistence of recession states and allow for multiperiod-ahead recession forecasting.

Another modern trend in the literature emphasizes the importance of the information available at the time a forecast is made. Miller (14) develops recession-probability models using real-time data and logistic regressions, illustrating how recession probabilities can be constructed using information available at the forecast date. This is particularly relevant when evaluating the forecasting performance of recession models, as historical macroeconomic data may later be revised.

The present study considers whether allowing the effects of explanatory variables to vary across economic regimes can provide additional information for recession forecasting. The objective is to compare a classical logit model with two regime-dependent alternatives—a threshold logit model and a smooth transition logit model—for forecasting recessions in Latvia. The analysis evaluates both explanatory fit and predictive performance. Particular attention is given to the role of inflation, manufacturing confidence, financial conditions, labour-market indicators, housing prices, exports, economic strain, and the COVID-19 period indicator, while the final specification is selected after considering correlations and multicollinearity. The study contributes to the Latvian literature by bringing together a conventional binary-response benchmark and nonlinear regime-dependent specifications within a common recession-forecasting framework. The comparison is based not only on in-sample measures such as the Akaike Information Criterion (AIC) and McFadden's pseudo-R^2, a likelihood-based measure of goodness of fit, but also on the Receiver Operating Characteristic curve (ROC-AUC) and recursive out-of-sample probability forecasts. This approach therefore assesses whether the regime-dependent specifications offer additional forecasting value relative to the classical logit benchmark.

The analysis is performed in R software (version 4.3.0). The program code is available on GitHub (15).

2 Materials and methods

2.1 Data sources and variable definition

The analysis is conducted using quarterly Latvian macroeconomic data for 2005Q3–2025Q4. The dependent variable is a binary recession indicator (R) which takes the value one when the economy satisfies the technical recession definition used in the study—two consecutive quarters of negative real Gross Domestic Product (GDP) growth—and zero otherwise. The indicator takes the value one starting with the first of two consecutive quarters of negative GDP growth and remains equal to one for both quarters, as well as for any subsequent quarters in which GDP growth remains negative. It should be noted that the recession indicator is defined ex post. Although the indicator is set to one from the first of two consecutive quarters of negative GDP growth, the recession status of the first quarter can only be confirmed once GDP growth for the subsequent quarter is observed. Thus, the recession indicator is used as an ex post outcome

for evaluating the forecasts and does not represent information available in real time at quarter t.

Quarterly GDP data are obtained from Eurostat (16). The resulting binary formulation makes logistic regression appropriate because the objective is to estimate the probability that a given quarter belongs to a recession period rather than to forecast the continuous level of GDP.

The explanatory variables were selected to represent several dimensions of economic activity and financial conditions. Inflation (I) is measured using the Harmonised Index of Consumer Prices (HICP) from Eurostat (17). Export (E) data are obtained from the Central Statistical Bureau of Latvia (CSB) (18). Manufacturing/business confidence (C) is represented by the CSB confidence indicator (19). The economic-strain measure (Tn) is obtained from the CSB database (20), while house-price dynamics (H) are taken from the CSB series on house-price changes (21). Unemployment (U) information is based on the CSB population-by-labour-status data (22). The three-month interbank interest-rate measure (R3) is obtained from Latvijas Banka (23). In addition, the model incorporates a COVID-19 indicator (Cov) based on the updated estimates of Holston et al. (24). Table 1 provides detailed information on the data used in the analysis. All data are publicly available and can be used without any additional licensing requirements.

The initial database therefore contains eight macroeconomic indicators together with the recession indicator. The variables are aligned to a common quarterly observation period. Where monthly indicators are used, the series are transformed or aggregated to quarterly frequency so that the timing of the explanatory variables is consistent with the quarterly recession indicator. Lagged variables are used where specified by the model to incorporate the delayed effect.

Chronologically, GDP and, respectively, recession become publicly available later than the values of the factors, with a delay, so we can make a forecast based on the contemporaneous factor values. All the data for the period till the end of 2025 are taken on May 11, 2026, so they were not revised after that. Accordingly, all revisions made before May 11 are included.

2.2 Preliminary statistical analysis

Before estimating the alternative logistic specifications, the explanatory variables are examined using pairwise correlation analysis and variance inflation factor (VIF) diagnostics. Correlation analysis is used to identify the strength of the

TABLE 1 Data description and transformations.

Variable	Original series	Original frequency	Source	Transformation	Units	Seasonal adjustment
Inflation (I)	Harmonised Index of Consumer Prices (HICP) (Latvia)	Monthly	Eurostat	Average of 3 month of a quarter	Moving 12 months average rate of change	No
Manufacturing confidence (C)	KRE020m	Monthly	CSB	Average of 3 month of a quarter	%	Yes
Unemployment (U)	NBA010c (Total, Unemployed)	Quartely	CSB	Unemployed/total	Unitless (ratio)	No
Three-month interbank interest rate (R3)	3-month RIGIBOR (2025–2013) and 3-month EURIBOR (2014–2025)	Monthly	Latvijas Banka	Average of 3 month of a quarter	%	No
Export (E)	ATD100c	Quartely	CSB	No	milj.euro	No
House price changes (H)	PCI050c3	Quartely	CSB	No	% of the corresponding period of the previous year	No
Economic Tension Indicator (Tn)	NNN040	Yearly	CSB	Taken the same value for all quarters of a year	%	No
COVID-19 indicator (Cov)	covid.ind (OxCGRT Stringency Index points, 0–100, quarterly average)	Quartely	Federal Reserve Bank of New York Staff Reports	No	Index points (0–100)	No
Recession	Real GDP growth (Latvia)	Quartely	Eurostat	Manual (1 from the 1st of two sequential GDP growth decreases)	Binary (0,1)	Yes

association between candidate predictors and the recession indicator and to detect strong relationships among explanatory variables. VIF diagnostics are used to assess multicollinearity. Variables that produce excessive collinearity are not retained together in the final specification, because severe multicollinearity can make coefficient estimates unstable and complicate economic interpretation. The confirmatory analysis with the Augmented Dickey–Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests is applied for data stationarity testing. The use of parsimonious specifications is particularly important given the relatively small quarterly sample.

2.3 Classical logit model

As the baseline specification, a classical logistic regression is estimated (25).

For observation t, the conditional probability of recession is represented as

$$P(R_t = 1 \mid X_{1t}, X_{2t}, \ldots, X_{kt}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt})}} \quad (1)$$

Where $p_{1t} = P(R_t = 1 \mid X_{1t}, X_{2t}, \ldots, X_{kt})$ is the probability of recession given the values of the explanatory variables; $R_t = 1 \mid X_{1t}, X_{2t}, \ldots, X_{kt} \sim Bernoulli(p_t)$, $X_{1t}, X_{2t}, \ldots, X_{kt}$ are the factors used in the study; and $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ are estimated coefficients. The odds are defined as $\frac{P(R_t = 1)}{1 - P(R_t = 1)}$, i.e., the ratio of the probability of recession to the probability of no recession.

Taking the natural logarithm of the odds transforms Equation 1 into the linear log-odds representation:

$$\ln\left(\frac{P(R_t = 1)}{1 - P(R_t = 1)}\right) = \beta_0 + \beta_1 X_{1t} + \ldots + \beta_k X_{kt} \quad (2)$$

The coefficients in a logit regression describe the effect of the explanatory variables on the log-odds of recession. Exponentiating a coefficient gives the corresponding odds ratio, which facilitates interpretation of the direction and magnitude of the estimated association. The classical logit specification assumes that the coefficients and therefore the marginal relationships remain constant over the full sample.

2.4 Threshold logit model

The first nonlinear specification is a threshold logit model. Following the threshold-model literature (1, 3), the logistic relationship is allowed to differ between two regimes defined by a transition variable. In the present application, the regimes are determined by the lagged manufacturing confidence indicator C_{t-1} and an estimated threshold c. Conditional on the explanatory variables, the recession indicator R_t follows a Bernoulli distribution with probability p_t. The log-odds equation is now written as:

$$\ln\left(\frac{P(R_t = 1)}{1 - P(R_t = 1)}\right) = \begin{cases} \beta_{10} + \beta_{11} X_{1t} + \ldots + \beta_{1k} X_{kt}, if \ C_{t-1} \le c, \\ \beta_{20} + \beta_{21} X_{1t} + \ldots + \beta_{2k} X_{kt}, if \ C_{t-1} > c \end{cases} \quad (3)$$

Thus, the coefficients are allowed to change when the transition variable crosses the threshold. This formulation captures discrete changes in the relationship between macroeconomic factors and recession probability across economic regimes. Threshold modelling is consistent with the nonlinear time-series framework developed by Tong (1) and with subsequent work on testing threshold effects (3).

2.5 Smooth transition logit model

The second nonlinear specification is a smooth transition logit model (STL). Unlike the threshold model, which changes coefficients abruptly at a single threshold, the smooth transition specification allows the coefficients to change gradually as the transition variable approaches and passes a threshold. The log-odds equation is formulated as:

$$\ln\left(\frac{P(R_t = 1)}{1 - P(R_t = 1)}\right) = \beta_{10} + \beta_{11} X_{1t} + \ldots + \beta_{1k} X_{kt} + G(C_{t-1}, c, \gamma)\left[\beta_{20} + \beta_{21} X_{1t} + \ldots + \beta_{2k} X_{kt}\right] \quad (4)$$

Where the logistic transition function is $G(C_{t-1}, c, \gamma) = \frac{1}{1 + e^{-\gamma(C_{t-1} - c)}}$, c is the threshold, and $\gamma > 0$ is the smoothness parameter. When γ is large, the transition becomes relatively abrupt and the model approaches a threshold-type relationship; lower values of γ imply a more gradual change between regimes. This formulation follows the smooth-transition framework developed by Teräsvirta (4, 5) and its application to logistic models (6).

2.6 Maximum likelihood estimation

For all three specifications, the log-likelihood has the common Bernoulli form:

$$\ell_m(\theta_m) = \sum_{t=1}^{T} \left[R_t \ln(p_{mt}) + (1 - R_t) \ln(1 - p_{mt}) \right], \quad m = 1, 2, 3 \quad (5)$$

Where p_{mt} denotes the conditional probability of recession for model m, with $m = 1$, $m = 2$, and $m = 3$ corresponding to the classical logit, threshold logit, and smooth transition logit models, respectively, and θ_m denotes the corresponding parameter vector: $\theta_1 = (\beta_0, \beta_1, \beta_2, \ldots, \beta_k)$,

$$\theta_2 = (\beta_{10}, \beta_{11}, \beta_{12}, \ldots, \beta_{1k}, \beta_{20}, \beta_{21}, \beta_{22}, \ldots, \beta_{2k}, c),$$

$$\theta_3 = \left(\beta_{10}, \beta_{11}, \beta_{12}, \ldots, \beta_{1k}, \beta_{20}, \beta_{21}, \beta_{22}, \ldots, \beta_{2k}, \gamma, c\right),$$

Model parameters are obtained by maximizing the likelihood function (25).

$$\hat{\theta}_m = \underset{\theta_m}{argmax}\, \ell_m\left(\theta_m\right) \tag{6}$$

For the threshold logit model, the threshold c is selected by a grid search over candidate values of the standardized transition variable. For each candidate threshold, the logistic regression coefficients are estimated by maximum likelihood, and the threshold having the highest log-likelihood is selected.

For the smooth transition logit model, the coefficient vectors, threshold c, and smoothness parameter γ are estimated simultaneously by numerical maximum likelihood using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm (6, 26).

The classical and threshold logit models are estimated using the *glm* maximum-likelihood procedure in R, while the smooth transition logit model is optimized numerically using BFGS. The nonlinear smooth-transition specification is initialized with starting values and optimized numerically because the threshold and smoothness parameters enter the likelihood nonlinearly. The explanatory and transition variables are standardized before estimating both nonlinear models to improve numerical convergence and ensure a common scale for parameter estimation and interpretation.

2.7 Model comparison measures

Model adequacy is assessed using Akaike Information Criterion (AIC), McFadden's pseudo-R^2, receiver operating characteristic (ROC) curves, and the area under the ROC curve (AUC). AIC is used to compare model fit while penalizing additional parameters (27); McFadden's pseudo-R^2 provides a likelihood-based measure of explanatory performance (28). ROC analysis evaluates the trade-off between sensitivity and specificity over alternative probability cutoffs, while AUC summarizes discriminatory ability (29). Sensitivity is the true positive rate, which in our study measures the proportion of actual recession quarters correctly identified by the model, while specificity measures the proportion of correctly classified non-recession quarters.

A formal statistical test of regime dependence is not performed. In the threshold specification, the threshold parameter is not identified under the null hypothesis of a constant-parameter logit model. So, a conventional likelihood-ratio test based on the standard chi-square asymptotic distribution is not directly applicable. Given the relatively small sample available for Latvia, the analysis therefore focuses on comparing the linear and regime-dependent specifications using complementary measures of model fit, discriminatory performance, and forecasting performance. Importantly, differences in AIC, McFadden's pseudo-R^2, and AUC are interpreted as evidence of differences in model fit and predictive discrimination rather than as a formal statistical rejection of the null hypothesis of parameter constancy. A formal bootstrap test of the threshold or nonlinearity effect would provide a natural extension of the present analysis.

To evaluate predictive performance beyond the estimation sample, a recursive 18-period out-of-sample forecasting procedure is conducted. The models are estimated using the observations available before the evaluation window, and recession probabilities are then generated sequentially for the 18 forecast quarters using the given values of the predictive factors. The lagged recession indicator is updated recursively using the model's own previous binary forecast, while the predictive factors during the evaluation window are taken at their given values. A conventional probability cutoff of 0.5 is used for binary classification. In addition to classification accuracy, probabilistic forecasts are evaluated using the Brier score (30) and mean absolute error (MAE). This combination of in-sample fit, discrimination, and out-of-sample probabilistic measures allows the classical and regime-dependent specifications to be compared from complementary perspectives.

3 Results and discussion

3.1 Data analysis and variable selection

The correlation analysis provides an initial assessment of the relationships between the explanatory variables and the recession indicator, as well as potential multicollinearity among the regressors. For the preliminary analysis, the data period for which all variables are defined is used (2007Q1–2021Q2). Paying attention to house price changes (H), the only variable whose values start from 2007, we indicate that despite exhibiting a

TABLE 2 The correlation matrix of factors with recession.

Factor\ Factor	R	E	C	I	R3	Tn	U	Cov
R	1	−0.2196	−0.6136	0.4276	0.4254	0.0009	0.1817	0.0777
E	−0.2196	1	0.1617	−0.6122	−0.7388	−0.816	−0.3008	0.4565
C	−0.6136	0.1617	1	−0.2828	−0.4694	−0.0604	−0.5312	−0.0586
I	0.4276	−0.6122	−0.2828	1	0.7871	0.2942	−0.1995	−0.209
R3	0.4254	−0.7388	−0.4694	0.7871	1	0.4426	0.168	−0.2141
Tn	0.0009	−0.816	−0.0604	0.2942	0.4426	1	0.5746	−0.5163
U	0.1817	−0.3008	−0.5312	−0.1995	0.168	0.5746	1	−0.1874
Cov	0.0777	0.4565	−0.0586	−0.209	−0.2141	−0.5163	−0.1874	1

significant negative correlation (−0.4985) with the recession indicator (R), H also has a strong correlation with other potential regressors. Therefore, we exclude house price changes from our analysis. Now all the variables have values from 2005, so the study uses the data period from 2005Q1 to 2025Q4, taking the first two quarters for possible lags, and 18 last quarters as the testing period. So, all tests, regressor choice, model specification choice, and model fit are completely based on data for the period 2005Q3–2021Q2.

As shown in Table 2, which represents the correlation matrix using the data for the mentioned period, manufacturing confidence (C) exhibits the strongest negative correlation, at approximately −0.614. In contrast, inflation (I) has the strongest positive correlation with the recession indicator, with a correlation coefficient of approximately 0.428. The three-month interbank interest rate (R3) is also positively correlated with recession, whereas export (E) exhibit some negative correlation, but unemployment (U) shows some positive correlation. The COVID-19 indicator (Cov) is positively associated with recession, although the magnitude of the correlation is relatively small. The Economic Tension Indicator (Tn) does not exhibit statistically significant correlation with the recession indicator. However, the regressors' relationship with one another suggests potential multicollinearity, which is confirmed by subsequent VIF diagnostics. Consequently, all these variables should not be included simultaneously without careful consideration of their joint effects. The preliminary analysis therefore motivated a more detailed analysis of multicollinearity before selecting the final model specification.

When testing data stationarity, some series got contradictory results. For some of them, there is not enough evidence to reject the Unit Root with the Augmented Dickey–Fuller test. The manufacturing confidence is stationary with at least 90% probability (Table 3).

For inflation, the ADF test failed to reject the unit-root null hypothesis, while the KPSS test rejected its null of stationarity. Before making a final conclusion regarding the stationarity of inflation, the test results should be interpreted in light of the relatively short quarterly sample. Both tests have well-known finite-sample limitations. The ADF test has low power against persistent but stationary alternatives, making it difficult to distinguish a highly persistent stationary process from a unit-root process in a small sample. In contrast, the KPSS test may reject the null hypothesis of stationarity too often in small samples. Therefore, rejection by the KPSS test and failure to reject by the ADF test should not, in this application, be interpreted as definitive evidence that inflation is non-stationary.

TABLE 3 Stationarity tests.

Variable	ADF test *p*-value	KPSS test *p*-value
Inflation (I)	0.7971	<0.01
Manufacturing confidence (C)	0.08474	>0.1
Unemployment (U)	0.2883	0.08236
Three-month interbank interest rate (R3)	0.4142	<0.01
Export (E)	0.6738	<0.01
Economic Tension Indicator (Tn)	0.8734	<0.01
COVID-19 indicator (Cov)	0.9153	0.03103
Recession (R)	0.3574	>0.1

The statistical evidence can be complemented by an economic consideration. The ECB's price-stability mandate anchors euro-area inflation expectations around its symmetric 2% medium-term target, providing an economic basis for treating inflation as a variable that fluctuates around a relatively stable long-run level, with deviations tending to dissipate over time (31). We therefore retain inflation in levels in the logistic specifications. This treatment should be understood as a modelling assumption supported jointly by the economic setting and the limitations of finite-sample stationarity testing, rather than as a formal conclusion about inflation's stationarity.

The initial model specification included a relatively large set of explanatory variables (Equation 7).

$$\ln\left(\frac{P(R_t=1)}{1-P(R_t=1)}\right)=-15.49+23.81I_t+7.35R_{t-1}+16.85C_{t-1}+32.88U_{t-1}-28.92Tn_{t-2} \quad (7)$$

This specification produced a relatively high McFadden's pseudo-R^2, approximately 0.77, and statistically significant coefficients. However, several VIF values were extremely large, indicating substantial multicollinearity. Although the model provided a strong in-sample fit, its coefficient estimates could not be interpreted reliably because of the strong dependence among the explanatory variables.

Alternative specifications were therefore considered to reduce multicollinearity. Replacing the second lag of the Economic Tension Indicator with its contemporaneous level reduced the model's explanatory power but also lowered the VIF values. Nevertheless, substantial multicollinearity remained. The final variable-selection procedure consequently focused on a more parsimonious specification using inflation and manufacturing confidence together with lags of the recession indicator.

3.2 Estimated classical logit model

After solving the multicollinearity problem, the classical logit model was estimated using the first lag of the recession indicator and the levels of inflation and manufacturing confidence (Equation 8).

$$\ln\left(\frac{P(R_t=1)}{1-P(R_t=1)}\right)=-2.65+2.69R_{t-1}+0.63I_t-0.91C_t \quad (8)$$

The model achieved a McFadden's pseudo-R^2 of 0.4959, an AIC of 37.6095, and an AUC of 0.9108. Importantly, the VIF diagnostics indicate that the final specification does not suffer from the severe multicollinearity observed in the larger initial model.

The estimated coefficients are economically interpretable. Inflation has a positive association with the probability of

recession, but higher manufacturing confidence is associated with a lower recession probability. The corresponding odds ratios are approximately 1.8834 for inflation and 0.4022 for confidence, which indicate that a one-unit increase in inflation increases the odds of recession, while a one-unit increase in confidence reduces them.

Although the classical logit model provides a reasonably strong predictive performance, it imposes constant marginal effects across all observations. This assumption may be restrictive because the effects of macroeconomic variables can differ depending on the prevailing economic conditions. The nonlinear specifications considered below address this limitation by allowing the relationships between the explanatory variables and recession probability to vary across regimes.

3.3 Estimated threshold logit model

Some improvement in model performance was obtained by introducing two regimes determined by the lagged manufacturing confidence indicator. The threshold logit model estimates separate logistic relationships depending on whether the lagged confidence indicator is below or above the threshold (Equation 9).

$$\ln\left(\frac{P(R_t=1)}{1-P(R_t=1)}\right)=\begin{cases}-2.36+3.08R_{t-1}+1.39I_t+0.17C_t, & \text{if } C_{t-1}\le 0.2321\\ 106.1-1592R_{t-1}-638.6I_t-820.8C_t, & \text{if } C_{t-1}>0.2321\end{cases} \quad (9)$$

The threshold parameter was searched over a grid defined by the 15th to the 85th percentiles of the threshold variable, with a resolution of one percentile point. Thus, the lowest and highest 15% of observations were excluded from the candidate threshold range to avoid excessively small regimes. For each candidate threshold, observations were assigned to the lower regime if $C_{t-1} \le threshold$ and to the upper regime otherwise. The threshold was then selected as the value that maximized the log-likelihood of the corresponding regime-dependent logistic model. Therefore, the reported threshold should be interpreted as a grid-based estimate.

The estimated threshold is 0.2321 standard deviations of the confidence variable. The variables were standardized before estimation to facilitate numerical convergence and to provide a common scale for the threshold variable. Some coefficients of the model appeared nonsignificant (Table 4), which can partly be explained by the relatively short series and rather large number of parameters. Relative to the classical logit model, the threshold specification produces a higher pseudo-R^2 and a lower AIC, which indicates improved model fit with a regime-dependent structure.

TABLE 4 Coefficient statistics of the threshold model reported in R.

Parameter	Estimate	Std. error	*z* value	Pr(>|z|)
Beta10	−2.355	0.8586	−2.743	0.0061
Beta11	3.079	1.376	2.237	0.0253
Beta12	1.394	0.8024	1.737	0.0824
Beta13	0.1736	1	0.174	0.8622
Beta20	106.1	2.25E+04	0.005	0.9962
Beta21	−1,592	4.95E+05	−0.003	0.9974
Beta22	−638.6	1.45E+05	−0.004	0.9964
Beta23	−820.8	1.73E+05	−0.005	0.9962

The estimated coefficients also demonstrate that the effects of the explanatory variables differ substantially between regimes. The first lag of the recession indicator has a positive effect on the current probability of recession in the first regime, indicating persistence in recession dynamics. Confidence has a small positive coefficient (0.1736), which could indicate higher recession odds, holding other variables constant. However, the coefficient is not statistically significant, limiting the interpretation of this effect. When confidence is below the estimated threshold, higher inflation is associated with a higher probability of recession. This relationship is consistent with the possibility that inflationary pressures during periods of weak confidence may coincide with adverse supply-side conditions and therefore signal increased recession risk. When confidence exceeds the threshold, the estimated effects of both inflation and confidence become strongly negative. These results show that the relationship between inflation and recession probability is conditional on the current confidence regime.

McFadden's pseudo-R^2 for the threshold model is 0.6648, which is larger than for the classical logit model (0.4959), but the AIC is 35.684, while the AUC is estimated as 0.9383. The model therefore provides some improvement in both explanatory and predictive performance.

The odds ratios further illustrate the regime-dependent effects. In the first regime, the estimated odds ratio for inflation is approximately 4.03, while that for confidence is approximately 1.19. In the second regime, they are almost insignificant. The values indicate that the magnitude and direction of the estimated effects differ according to the prevailing confidence regime.

The very large standard errors in the upper regime require a more specific statistical interpretation than simply explaining them by the short overall sample. For regime-specific logistic regression, the relevant information size is not the total number of observations alone but the number of outcome events available within each regime. Although the threshold model uses 64 observations, the estimated regimes are highly unbalanced: the lower regime contains 41 observations, including 9 recession observations, whereas the upper regime contains only 23 observations, including only 2 recession observations. Thus, the effective sample size for estimating the recession-related coefficients in the upper regime is much smaller than the total sample size. In addition, the logistic likelihood contains relatively little information about how the explanatory variables distinguish recession from non-recession observations within this regime. Under such sparse within-regime information, the maximum-likelihood estimates can become weakly identified and highly sensitive to individual observations, producing very large coefficient estimates and standard errors. This pattern is consistent with the extremely large standard errors reported for the upper-regime coefficients in Table 4. Therefore, these coefficients should not be interpreted as reliable estimates of the magnitude of regime-specific effects; rather, the results provide evidence that the data support differences in model fit across regimes more strongly than they support precise estimation of every regime-specific coefficient.

TABLE 5 Coefficient statistics of the STL model reported in R.

Parameter	Estimate	Std. error	*z* value	Pr(>|z|)
beta10	−2.5755	0.885	−2.91	0.0036
beta11	2.0432	1.6736	1.2209	0.2221
beta12	1.006	0.7817	1.2869	0.1981
beta13	−0.6396	1.2359	−0.5175	0.6048
beta20	73.3158	83.022	0.8831	0.3772
beta21	138.87	258.65	0.5369	0.5913
beta22	−21.7634	25.1492	−0.8654	0.3868
beta23	−296.36	344.53	−0.8602	0.3897
gamma	207.83	460.85	0.451	0.652
threshold	0.2454	0.03	8.1617	2.22E−16

3.4 Estimated smooth transition logit model

To allow the transition between regimes to occur gradually rather than instantaneously, a smooth transition logit model was estimated using the same explanatory variables (Equation 10).

$$\ln\left(\frac{P(R=1)}{1-P(R=1)}\right) = -2.58 + 2.04\,R_{t-1} + 1.01I_t - 0.64\,C_t + \frac{1}{1+e^{-207(C_{t-1}-0.245)}}\left[\begin{matrix}73.32+138.87R_{t-1}\\ -21.76I_t - 296.36\,C_t\end{matrix}\right] \quad (10)$$

The smooth-transition logistic model was estimated by numerical maximization of the log-likelihood using the BFGS algorithm. Convergence was assessed using the optimization convergence criterion. To assess sensitivity to the choice of starting values, alternative initial values for the nonlinear transition parameters were also considered. All tested specifications converged and produced similar likelihood values; the reported estimates correspond to the specification with the highest maximized log-likelihood. Unfortunately, many coefficients of the model appeared nonsignificant (Table 5). The same pattern as in the threshold model, although less extreme, is visible in the smooth-transition specification. Several regime-specific coefficients and the smoothness parameter have standard errors that are large relative to their point estimates. This suggests that the instability is not specific to the threshold estimation algorithm but is related more generally to the limited information available for identifying regime-specific nonlinear effects. In this sense, the threshold and smooth-transition models provide a useful illustration of the same dilemma in a small sample: increasing model flexibility can reveal regime dependence at the level of fitted probabilities while simultaneously making individual nonlinear parameters difficult to estimate precisely.

The smooth transition model achieves the highest McFadden's pseudo-R^2 among the three specifications, at approximately 0.6862, and AUC is 0.9468. However, its AIC is 38.4288. Thus, although the smooth transition specification provides a modest improvement in explanatory power over the threshold model, it does not achieve a better overall balance between predictive performance and model complexity.

The signs of the estimated coefficients are broadly consistent with those obtained from the threshold model, as we can see by comparing regime equations (Equations 11, 12) coming from (Equation10) with the threshold model (Equation 9).

$$\text{Regime 1:}\quad \ln\left(\frac{P(R=1)}{1-P(R=1)}\right) = -2.58 + 2.04R_{t-1} + 1.01I_t - 0.64\,C_t \quad (11)$$

$$\text{Regime 2:}\quad \ln\left(\frac{P(R=1)}{1-P(R=1)}\right) = 70.74 + 140.91R_{t-1} - 20.75I_t - 297\,C_t \quad (12)$$

The odds ratios provide an additional interpretation of the magnitude of these effects. In the first regime, the estimated coefficient for inflation corresponds to an odds ratio of approximately 2.75, while the coefficient for confidence corresponds to an odds ratio of approximately 0.53. In the second regime, the estimated odds ratios for inflation and confidence are close to zero.

These results indicate differences in the estimated relationships across regimes. At the same time, the very large magnitude of some estimated effects should be interpreted with caution given the relatively small sample size and the complexity of the nonlinear specification.

The model produces an estimated transition threshold of approximately 0.245 and a huge smoothness parameter of approximately 207. The high value of the smoothness parameter indicates that the estimated transition is almost abrupt and therefore resembles the threshold specification. The estimated smoothness parameter is important for interpreting the comparison between the nonlinear specifications. Because a large value of γ makes the transition function change rapidly around the estimated threshold, the fitted smooth-transition model is empirically close to a discrete threshold model in this sample. Thus, although the STL specification is theoretically more flexible because it permits gradual changes in coefficients, the data provide little evidence for a genuinely gradual transition. The similarity is also reflected in the comparable regime distribution: when observations are classified according to the estimated transition point, with $C_{t-1} \le 0.245$ and $C_{t-1} > 0.245$, the lower regime contains 42 observations, including 9 recession observations, whereas the upper regime contains 22 observations, including only 2 recession observations. The STL model should therefore not be interpreted as providing strong evidence for a distinct smooth-transition mechanism in this sample. Rather, its results suggest that the additional flexibility of the smooth-transition formulation is largely used to approximate an abrupt regime change.

This finding changes the interpretation of the three-model comparison: the classical logit provides the constant-parameter benchmark, but the threshold and STL specifications are empirically more likely to represent the same underlying regime-dependent relationship than the model labels alone would suggest. The comparison therefore provides stronger evidence for the usefulness of allowing regime dependence than for a substantive advantage of a smooth transition over a discrete threshold.

TABLE 6 The three model comparisons.

Model	AIC	Pseudo-R^2	AUC
Classical logit	37.6095	0.4959	0.9108
Threshold logit	35.684	0.6648	0.9383
Smooth transition logit	38.4288	0.6862	0.9468

3.5 Comparison of model performance

The overall performance of the three models is summarized in Table 6.

The in-sample fit results indicate that both nonlinear regime-dependent models outperform the classical logit specification. The classical logit model has the lowest pseudo-R^2 and AUC. The threshold logit model achieves the lowest AIC, while the smooth transition model provides the highest McFadden's pseudo-R^2 and AUC.

These results suggest that allowing the effects of macroeconomic variables to vary across economic regimes improves the model's in-sample fit, its ability to distinguish recession from non-recession quarters. The smooth transition specification provides the best overall compromise between model fit, complexity, and interpretability. Although the threshold model achieves the lowest AIC, smooth transition model's additional parameter does translate into superior pseudo-R^2 and AUC performance.

An important statistical implication of the comparison is that regime dependence can improve model fit without necessarily providing precisely estimated regime-specific coefficients. This distinction is particularly relevant in small samples with rare binary events. In the present application, recession observations make up a relatively small fraction of the estimation sample, and the imbalance becomes substantially stronger after the sample is divided into regimes. The upper regime contains only two recession observations in the threshold specification and two recession observations in the corresponding smooth-transition classification. Consequently, introducing regime-specific coefficient vectors substantially reduces the amount of information available for estimating the effects associated with recession events. The results illustrate a general small-sample trade-off: allowing coefficients to vary across regimes can capture nonlinear structure and improve in-sample discrimination, but it can also increase estimation uncertainty when some regime contains few events. Thus, improvements in AIC, pseudo-R^2, or AUC should not automatically be interpreted as evidence that all regime-specific coefficients are reliably estimated. In applications with similarly rare outcomes, model comparison and forecasting performance may be more informative than the individual significance and magnitude of highly unstable regime-specific coefficients.

The comparison also illustrates an important distinction between in-sample information criteria and out-of-sample forecasting performance. The threshold logit model has the lowest AIC in the estimation sample, whereas the smooth-transition logit model achieves the best out-of-sample Brier score and MAE. Thus, the ranking based on AIC does not coincide with the ranking based on probabilistic forecasting performance. This divergence is not necessarily contradictory because the two types of measures evaluate different properties of a model. AIC is a likelihood-based in-sample criterion that balances goodness of fit against model complexity. It is not a direct estimate of performance on a future forecasting sample.

The distinction is particularly relevant in the present application. The estimation sample is relatively small, recession observations are rare, and the regime-dependent specifications allocate observations across separate regimes. In the threshold model, the lower regime contains 41 observations including 9 recession observations, whereas the upper regime contains only 23 observations including only 2 recession observations. Consequently, the nonlinear specification can obtain a substantial improvement in in-sample likelihood by adapting to regime-specific patterns while simultaneously estimating some parameters from very limited event information. Such flexibility can improve the in-sample information criterion without necessarily improving performance on future observations.

The results therefore suggest that AIC is useful as a measure of penalized in-sample fit but should not be used as the sole model-selection criterion in this setting. This is especially important when the sample is small relative to model complexity. Small-sample corrections to information criteria, such as AICc, can provide an additional robustness check, while out-of-sample probabilistic measures such as the Brier score and MAE directly assess forecasting performance. In the present study, the lower Brier score and MAE of the smooth-transition model provide descriptive evidence that its additional flexibility translated into better probability forecasts over the evaluation window, even though the threshold model achieved the best in-sample AIC. However, this reversal should be interpreted as evidence of different model rankings across evaluation criteria rather than as definitive evidence that one model dominates the others.

3.6 ROC curve analysis

ROC curve analysis was used to further compare the discriminatory performance of the three models. As we see in Figure 1, all three ROC curves lie above the diagonal line, indicating better performance than random guessing. Comparing the three model curves, the smooth transition logit performs slightly better overall, having an AUC of 0.9468, but the threshold model follows closely with an AUC of 0.9383. The classical logit model has a lower, but still relatively strong, AUC of 0.9108.

The ROC results are consistent with pseudo-R^2 comparison and reinforce the conclusion that incorporating regime dependence improves recession classification. The relatively small difference between the threshold and smooth transition models also suggests that both nonlinear specifications provide robust discriminatory performance. Nevertheless, the smooth transition model has an advantage because it achieves the highest AUC while also having the highest pseudo-R^2 despite having lower AIC.

In practical terms, the choice of classification threshold determines the relative importance assigned to missed recessions and false recession signals. A lower threshold generally increases sensitivity at the expense of specificity, whereas a higher threshold tends to reduce false positives but may result in more missed recession observations. Therefore, the preferred cutoff should ultimately depend on the intended application of the forecasting model.

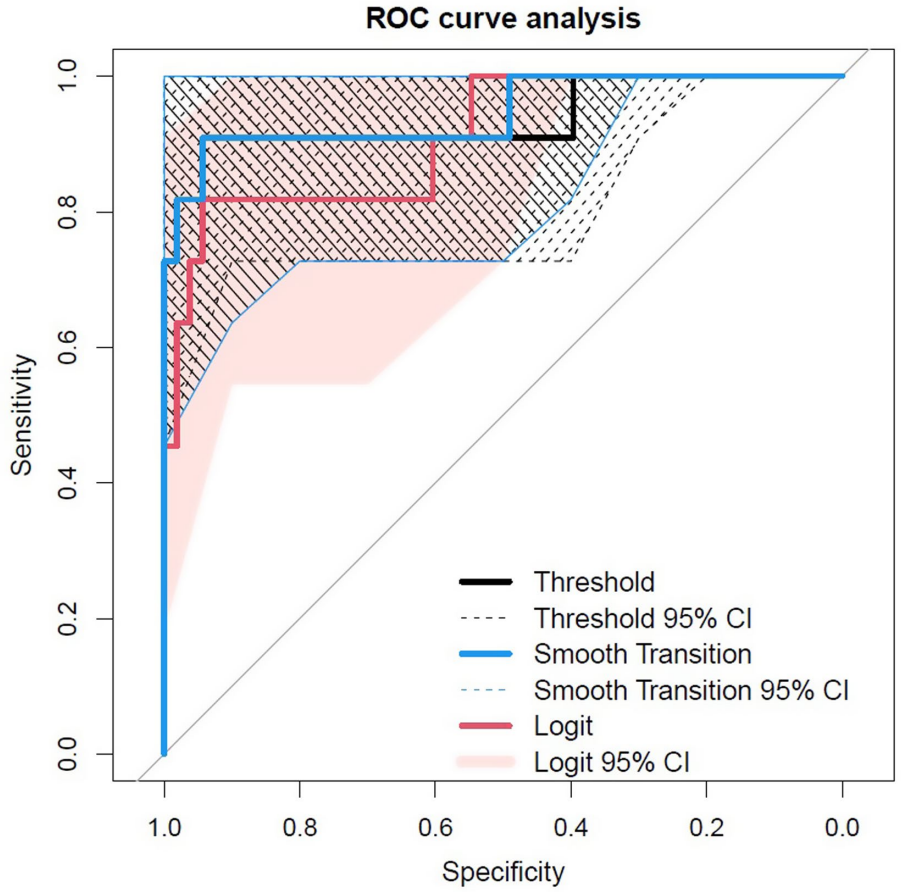


FIGURE 1
ROC curves of the three models with confidence bands.

3.7 Forecast comparison

To assess the out-of-sample forecasting performance of the three models, an 18-quarter recursive multi-step forecasting exercise with fixed model parameters was conducted for quarters 65–82. The models were estimated once using observations from quarters 1–64 only, while quarters 65–82 were reserved exclusively for out-of-sample evaluation. The estimated coefficients and, for the nonlinear models, the estimated nonlinear parameters were kept fixed throughout the forecasting period and were not re-estimated at each forecast step. At each step, the recession probability was calculated using the information available at the forecast origin. The resulting probability was evaluated against the recession indicator subsequently determined from GDP growth. Thus, the recession indicator represents the ex post outcome and was not treated as information available at the forecast origin. The lagged recession indicator was then updated recursively using the preceding forecast. Specifically, the predicted recession probability was first converted into a binary recession indicator using a conventional 0.5 cutoff: probabilities of at least 0.5 were classified as recession ($R = 1$), while probabilities below 0.5 were classified as non-recession ($R = 0$). This binary forecast was then used as the lagged recession indicator for the subsequent forecast period. Thus, the recursive element of the forecasting procedure concerns the updating of the lagged dependent variable, while the model parameters remain fixed. Thus, our 18-step-ahead recession forecast is conditional on knowing the values of the inflation and confidence variables. Predicting the future values of these explanatory variables is therefore not part of the present analysis. The predicted recession probabilities are presented graphically in Figure 2.

The forecasts exhibit similar patterns in the second part of the forecast window and detect the second recession period of 2023Q2–2023Q4 (periods 72–74 in the ex post recession indicator) relatively well. The logit model does not predict the first recession period of 2021Q4–2022Q3, showing only a gradual increase in the recession probability towards 2023Q2. The threshold model also does not distinguish between the two actual recession periods, instead indicating a longer second recession period that starts earlier. Finally, the smooth transition model raises the recession probability to one in the middle of the first true recession period, followed by a small sequential decrease and then another increase. It predicts the second recession period two quarters in advance, similarly to the threshold model. The forecast probabilities from all three models subsequently decline as the evaluation window moves into a long period of non-recession quarters. However, the smooth transition model indicates the end of the recession earlier, suggesting a faster recovery than the threshold and logit models. Nevertheless, both threshold-dependent models fail to identify the two-quarter non-recession period between the two recession periods when a 0.5 classification threshold is used.

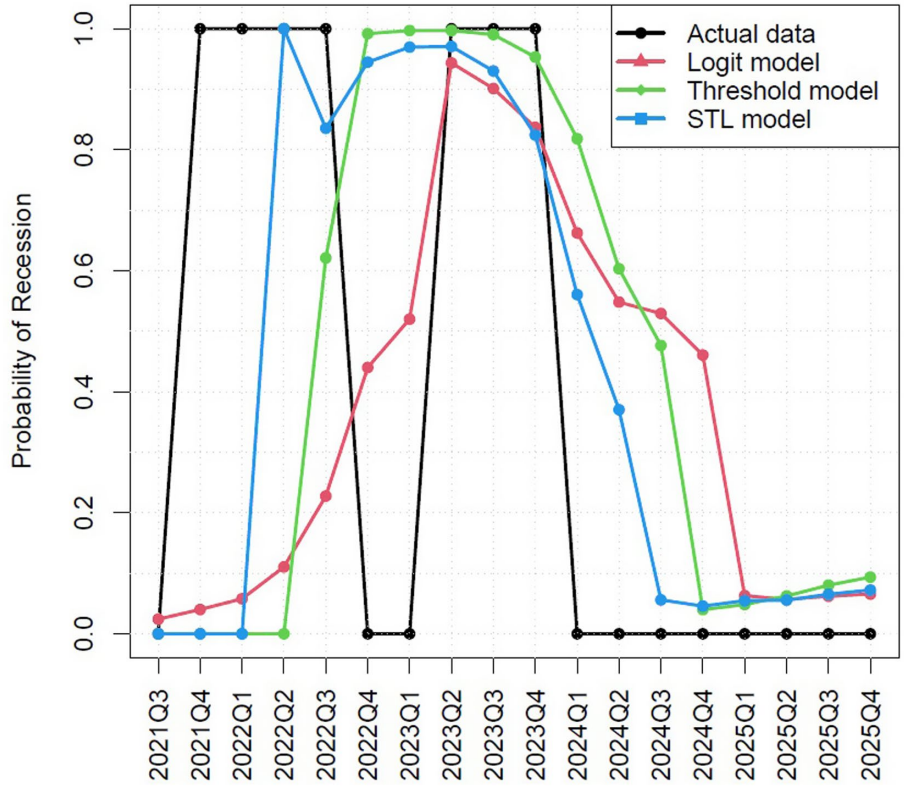


FIGURE 2
Recession probability by the three models (Logit, Threshold, and STL) comparison with actual data (1 – recession, 0 – no recession).

TABLE 7 Out-of-sample forecast performance over the period 2021Q3–2025Q4.

Model type	R_t on R_{t-1}, $C_{t,\,lt}$ (threshold = C_{t-1})		R_t on R_{t-1}, $Tn_{t,\,lt}$ (threshold = Tn_{t-1})	
	Brier score	MAE	Brier score	MAE
Classical logit	0.275	0.4064	0.4819	0.6134
Threshold logit	0.356	0.425	0.5527	0.6141
Smooth transition logit	0.2427	0.313	0.5163	0.5491

Using this cutoff, the logit model correctly classifies 3 recession quarters and 6 non-recession quarters, while the threshold model correctly classifies 4 recession quarters and 7 non-recession quarters. The smooth transition logit model correctly classifies 5 recession quarters and 8 non-recession quarters. The corresponding accuracy rates are 0.556, 0.611, and 0.722, respectively.

The probabilistic forecast errors also provide an informative comparison than classification accuracy alone. The STL model has the lowest Brier score (0.2427), followed by the classical logit model (0.2749) and then the threshold model (0.356) (Table 7). The same ordering is obtained using mean absolute error: 0.313 for STL, 0.4064 for the logit model, and 0.425 for the threshold model. Lower values indicate better probabilistic forecasts. Therefore, over the 18-period evaluation window, the STL model provides the best probabilistic forecast performance among the three specifications. However, the lower Brier score and MAE of the STL model should be interpreted as descriptive evidence rather than conclusive evidence of strong forecast superiority. The AUC value calculated from the 18-period out-of-sample forecast probabilities is only 0.4026 for the classical logit models, with 95% confidence intervals of (0.1299; 0.7273) based on 5,000 stratified bootstrap replicates. The threshold model forecast got a 0.5 AUC with 95% confidence intervals of (0.1818; 0.8117). The STL model yields an AUC of 0.6623, with 95% confidence intervals of (0.3506; 0.9481). This result should nevertheless be interpreted cautiously because the evaluation sample contains only 18 observations, including just two recession periods, and the estimated AUC may therefore be sensitive to the small sample.

The out-of-sample AUC of 0.4026 for the classical logit also deserves interpretation beyond the uncertainty associated with the small evaluation sample. An AUC of 0.5 corresponds to random ranking of recession and non-recession observations, whereas an AUC below 0.5 indicates that, in the particular evaluation sample, the model's ranking of predicted recession probabilities was worse than random ranking. Thus, the point estimate of 0.4026 indicates poor realized discriminatory performance of the classical logit over this 18-quarter forecast window. This is qualitatively different from

TABLE 8 Summary of the confusion matrices for the three models at a cutoff of 0.5.

Actual vs Forecast	Logit	Threshold	STL
Actual 0, Forecast 0	7	7	8
Actual 0, Forecast 1	4	4	3
Actual 1, Forecast 0	4	3	2
Actual 1, Forecast 1	3	4	5

TABLE 9 Comparison of sensitivity, specificity, and accuracy for the three models at a cutoff of 0.5.

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
Logit	42.9	63.6	55.6
Threshold	57.1	63.6	61.1
STL	71.4	72.7	72.2

imprecision alone: the point estimate lies below the random-ranking benchmark. However, the AUC estimate should not be interpreted as evidence that the classical logit has systematically worse-than-random discriminatory ability. The 95% bootstrap confidence interval is very wide, and includes 0.5. The evaluation sample contains only 18 observations and two recession periods, so the AUC is based on very few recession/non-recession comparisons and can be highly sensitive to individual observations. The appropriate interpretation is therefore that the classical logit exhibited poor ranking performance in this particular out-of-sample window, while the available data are insufficient to establish that its population-level discriminatory ability is below 0.5. The binary classification performance of the out-of-sample results is analyzed using the conventional 0.5 cutoff. The confusion matrices for the three models are summarized in Table 8, while the classification performance measures are presented in Table 9. As shown in Table 9, the STL model achieves the highest accuracy, whereas the logit model has the lowest accuracy. The logit model has relatively low recession sensitivity of 42.9%, specificity of 63.6%, and overall accuracy of 55.6%. The threshold model performs slightly better, with recession sensitivity of 57.1%, the same specificity of 63.6%, and overall accuracy of 61.1%. Finally, the STL model performs best, with recession sensitivity of 71.4%, specificity of 72.7%, and overall accuracy of 72.2%.

The models also differ in the quality of their probability forecasts. The STL model achieves the lowest Brier score and MAE and the highest forecast AUC, while the threshold model performs better than the classical logit model in terms of AUC. For the robustness analysis of the forecasts, models with another factor set are tried, namely, the Confidence factor is replaced by the Economic Tension Indicator both as a regressor (Tn_t) and a threshold (Tn_{t-1}). As we can see in Table 7, the Brier score and MAE became worse for all models specifications.

The results therefore suggest that regime-dependent nonlinear specifications may be useful for forecasting recession probabilities, although further evidence from a longer sample period would be needed to assess their forecasting performance more reliably.

4 Conclusion

This study, using quarterly data from 2005 to the end of 2025, examines how well classical and nonlinear logit models can forecast recession dynamics in Latvia. The results indicate that allowing the effects of macroeconomic variables to vary across economic regimes improves model in-sample performance compared with the classical logit specification.

Among the considered explanatory variables, inflation and manufacturing confidence are found to be the most informative predictors of recession probability. Inflation was generally associated with a higher probability of recession, but higher manufacturing confidence was associated with lower recession risk. The first lag of the recession indicator also appeared to be an important component of the forecasting specification.

The analysis demonstrated that multicollinearity consideration is important in the specification of recession models. Although a larger initial model achieved a relatively high pseudo-R^2, its very large VIF values limited the reliability of coefficient interpretation. Reducing the set of explanatory variables resulted in a more parsimonious specification without multicollinearity while having moderate predictive performance.

Overall, the threshold and smooth transition specifications provide some empirical evidence that recession probabilities can benefit from regime-dependent relationships. The STL model is reported to have the best out-of-sample probability measures Brie score and MAE, but the small evaluation sample means that this result should not be interpreted as definitive evidence of forecast dominance.

Several limitations should be considered when interpreting our findings. The analysis is based on a relatively small quarterly sample, which constrains the complexity of the models that can be estimated reliably and may affect the precision of nonlinear parameter estimates. In addition, the selection of explanatory variables was constrained by multicollinearity among several macroeconomic indicators. The results should therefore be interpreted as evidence of predictive relationships rather than causal effects.

From a statistical perspective, the results highlight an important limitation of regime-dependent logistic models in small samples with rare events. Splitting the observations into regimes can substantially reduce the effective number of recession observations available for estimating regime-specific parameters. In the present case, only two recession observations fall into the upper regime, and the corresponding threshold-model coefficients have extremely large standard errors. This indicates that regime-dependent models may detect a useful change in predictive structure while simultaneously providing weakly identified estimates of individual regime-specific effects. Therefore, in small samples, parameter magnitude and statistical significance should be interpreted more cautiously than aggregate measures of predictive performance, and model comparisons should place greater emphasis on out-of-sample probability forecasts and their uncertainty.

The estimated smoothness parameter provides a second methodological lesson. The value of approximately 207 indicates that the smooth-transition specification approaches an abrupt threshold transition in this sample. Consequently, the empirical distinction between smooth and discrete regime dependence is weak, and the principal statistical finding is not that a smooth transition is superior to a threshold specification, but that allowing the relationship between predictors and recession probability to vary

across regimes can improve model fit and probabilistic forecasting relative to a constant-parameter logit. These findings illustrate the importance of considering both model flexibility and parameter identifiability when applying nonlinear logistic models to short time series with imbalanced binary outcomes.

Future research could extend the analysis in several directions. First, more explanatory variables and alternative models could be considered. Second, alternative transition functions for regime specifications could be tried to assess whether they provide additional improvements in prediction, including asymmetric transitions between regimes. Third, the models could be tested using data from other Baltic economies, particularly Lithuania and Estonia, to check the robustness and generalizability of the findings. Finally, additional out-of-sample validation would be useful over different economic periods.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

OP: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. JF: Conceptualization, Data curation, Validation, Writing – original draft, Writing – review & editing, Investigation, Software.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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References

1. Tong H. *Threshold Models in Non-linear Time Series Analysis*. New York: Springer (1983).

2. Aydin D, Mermi S. Some regime-switching models for economic time series: a comparative study. *Eskisehir Tech Univ J Sci Technol A Appl Sci Eng.* (2022) 23:48–69. doi: 10.18038/estubtda.881251

3. Lee S, Seo M, Shin Y. Testing for threshold effects in regression models. *J Am Stat Assoc.* (2010) 106:220–31. doi: 10.1198/jasa.2011.tm09800

4. Teräsvirta T, Anderson HM. Characterizing nonlinearities in business cycles using smooth transition autoregressive models. *J Appl Econ.* (1992) 7:S119–36. doi: 10.1002/jae.3950070509

5. Terasvirta T. Specification, estimation, and evaluation of smooth transition autoregressive models. *J Am Stat Assoc.* (1994) 89:208. doi: 10.2307/2291217

6. Hurn AS, Silvennoinen A, Teräsvirta T. A smooth transition logit model of the effects of deregulation in the electricity market. *J Appl Econ.* (2016) 31:707–33. doi: 10.1002/jae.2452

7. Pavlenko O, Matvejevs A. Comparison of linear and nonlinear models for forecasting of food commodity prices in Latvia. In *22nd International Scientific Conference "Engineering for Rural Development": Proceedings, Vol. 22*. Jelgava: Latvia University of Life Sciences and Technologies (2023). 735–744. doi: 10.22616/ERDev.2023.22.TF145

8. Pavlenko O. Star time series models with asymmetric transition function: estimation using R software and applications for Latvian economic data. *24th International Scientific Conference "Engineering for Rural Development": Proceedings, Vol. 24*. Jelgava: Latvia University of Life Sciences and Technologies (2025). 457–462. doi: 10.22616/ERDev.2025.24.TF096

9. Pavlenko O, Zeltina L. The second order logistic smooth transition autoregressive model for unemployment rate of Latvia. *Proceedings of the 2024 IEEE 65th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS 2024), 3–4 October, 2024*. Latvia, Riga: IEEE (2024). 41–45. doi: 10.1109/ITMS64072.2024.10741945

10. Pavlenko O. The smooth transition autoregressive models for the unemployment rate of Latvia. *Front Appl Math Stat*. (2025) 11:1673247. doi: 10.3389/fams.2025.1673247

11. Budkuna N, Matvejevs A, Pavlenko O. Determinants of Degree Completion in Financial Engineering at Riga Technical University. *Proceedings of the 2025 IEEE 66th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS 2025)* (2025). Riga, Latvia 1–5. doi: 10.1109/ITMS67030.2025.11236506

12. Estrella A, Mishkin FS. Predicting U.S. recessions: financial variables as leading indicators. *Rev Econ Stat*. (1998) 80:45–61. doi: 10.1162/003465398557320

13. Kauppi H, Saikkonen P. Predicting U.S. recessions with dynamic binary response models. *Rev Econ Stat.* (2008) 90:777–91. doi: 10.1162/rest.90.4.777

14. Miller DS. Predicting Future Recessions. FEDS Notes, Board of Governors of the Federal Reserve System (2019)

15. R code developed for the analyses. Available online at: https://github.com/Oksana-Pavlenko/Recession-Modelling-data-and-code/blob/main/Frontiers-2026-Recession-Modelling-Forecasting.R (Accessed October 18, 2026).

16. Eurostat. *Gross domestic product (GDP) and main Components (Output, Expenditure and Income)—Quarterly data*. Luxembourg: Eurostat (2026).

17. Eurostat. *Harmonised index of Consumer Prices (HICP)—Monthly data (Indices and rates of change)*. Luxembourg: Eurostat (2026).

18. Central Statistical Bureau of Latvia. *The data of export*. Riga: Central Statistical Bureau of Latvia (2026).

19. Central Statistical Bureau of Latvia. *The data of Confidence Indicators*. Riga: Central Statistical Bureau of Latvia (2026).

20. Central Statistical Bureau of Latvia. *Economic Strain among Persons (per cent), 2005–2025*. Riga: Central Statistical Bureau of Latvia (2026).

21. Central Statistical Bureau of Latvia. *House price Changes (% over the Corresponding period of Previous year)*. Riga: Central Statistical Bureau of Latvia (2026).

22. Central Statistical Bureau of Latvia. *Population by labour status (unemployment)*. Riga: Central Statistical Bureau of Latvia (2026).

23. Latvijas Banka. *Interest rates*. Riga: Latvijas Banka (2026).

24. Holston K, Laubach T, Williams JC. Measuring the Natural Rate of Interest after COVID-19. Federal Reserve Bank of New York Staff Reports, no. 1063, (June 2023). https://www.newyorkfed.org/research/policy/rstar/ (Accessed May 16, 2026).

25. Hosmer DW, Lemeshow S. *Applied Logistic Regression: Second Edition*. New York: John WIley & Sonc, Inc. (2000).

26. Kavkler A, Mikek P, Böhm B, Boršič D. Nonlinear Econometric Models: the Smooth transition Regression Approach (2008). Available online at: https://www.researchgate.net/publication/228556576 (Accessed May 5, 2024).

27. Enders W. *Applied Econometric Time Series*. Fourth, 4th edition ed. Hoboken, New Jersey, USA: Wiley (2014) 978-1118808566 1118808568.

28. Allison PD. *Measures of Fit for Logistic Regression*. Philadelphia, Pennsylvania, USA: Statistical Horizons LLC and the University of Pennsylvania.

29. Fawcett T. An introduction to ROC analysis. *Pattern Recogn Lett*. (2006) 27:861–74. doi: 10.1016/j.patrec.2005.10.010

30. Brier GW. Verification of forecasts expressed in terms of probability. *Mon Weather Rev*. (1950) 78:1–3. doi: 10.1175/1520-0493(1950)078<>2.0.CO;2

31. European Central Bank. The ECB'S Monetary Policy Strategy Statement (2025). Available online at: https://www.ecb.europa.eu/mopo/strategy/strategy-review/ecb.strategyreview202506_strategy_statement.en.html (Accessed October 17, 2026).