Prague Economic Papers
2025, Volume 34, Issue 3
https://doi.org/10.18267/j.pep.897

PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

Assessing the Early Warning Capabilities of GaR: A Probabilistic Approach to Recession Detection in CEE Economies

Gheorghe-Alexandru Tarta

Bucharest University of Economic Studies, Romania

e-mail: alexandru.tarta@fin.ase.ro

Abstract

This paper introduces a novel application of Growth-at-Risk (GaR) as an early warning system (EWS) for predicting recessions. By transforming GaR into a classification model, we assess its ability to signal economic downturns across 11 Central and Eastern European (CEE) economies from 2005 to 2024. We compare GaR's performance with logistic regression across eight forecasting horizons. Our findings indicate that GaR slightly outperforms the logit model when financial conditions are used as the primary predictor. However, when additional factors such as agents' expectations and financial flows are incorporated, the performance gap narrows. Our results suggest that Growth-at-Risk can function as an effective early warning system without significant performance trade-offs, while offering a flexible and theoretically grounded alternative. Policymakers can leverage Growth-at-Risk not only as a tail risk instrument but also as a classifier, enhancing their forecasting capabilities.

Keywords: Growth-at-Risk, early warning systems, financial conditions, recession probability

JEL Classification: C18, E44, G01

1. Introduction

This paper explores how financial conditions shape the distribution of future economic activity, with a focus on estimating the probability of recession in Central and Eastern European (CEE) economies. In recent years, the Growth-at-Risk (GaR) framework has gained prominence as a forward-looking tool that estimates the full conditional distribution of GDP growth based on financial and macroeconomic indicators. Originally developed by Adrian, Boyarchenko, and

Giannone (2019), the GaR approach is typically used to quantify macro-financial vulnerabilities by focusing on adverse tail quantiles such as the 5th or 10th quantiles. However, despite delivering a full parametric distribution, GaR is most often used solely to assess the intensity of downside risks, while its potential to estimate the probability of a negative GDP gap or growth, indicating a recession, remains largely untapped. This question is traditionally examined through early warning systems (EWS); in this paper, we propose reframing the Growth-at-Risk (GaR) framework, typically employed as a tail-risk quantification tool, into a forward-looking early warning model for estimating recession probabilities, by extracting and repurposing the full informational content embedded in the estimated distribution.

Economic policymaking often becomes binary in times of heightened uncertainty. Under volatile conditions, point forecasts lose reliability, and policymakers increasingly rely on clear signals about turning points in the business cycle to guide discretionary interventions. Whether anticipating a "soft" or "hard" landing, central banks, from the European Central Bank's "whatever it takes" era to the Federal Reserve's recent communications, require forward-looking tools that can effectively indicate the risk of recession. In this context, binary early-warning systems (EWS) have become essential. Recent contributions by Grab and Titzck (2020), Fonseca et al. (2023), and Bussière and Lhuissière (2024), among others, reflect a growing interest in predicting regime shifts using financial conditions. We contribute to that literature by proposing a reinterpretation of the GaR framework, traditionally used for tail-risk assessment, as a binary early-warning model that estimates the probability of recession using the full conditional distribution of GDP deviation from potential.

Our contribution within the literature is twofold. First, we advocate for a broader interpretation of GaR outputs, highlighting their ability to inform about the full distribution of future economic outcomes, including the probability of recession, rather than just tail events. Second, we empirically implement this reinterpretation for CEE economies testing various modelling strategies across financial conditions and macro-financial variables. In doing so, we provide new evidence on the early-warning capabilities of GaR for emerging economies.

This perspective is particularly important for the CEE region, where business cycle volatility and data constraints often hinder the timely identification of turning points. Policymakers in these economies frequently face challenges in assessing whether positive output gaps are genuinely closing, or whether the economy has already slipped into recessionary territory, especially in real time. In such a context, relying solely on point estimates or revised GDP data may delay critical policy responses. A probabilistic approach, such as the GaR framework, enriched with region-specific financial condition proxies, external imbalances, and macro-financial vulnerability indicators, offers a valuable complement. By providing forward-looking recession probabilities, this method enhances the information set available to policymakers and supports more responsive, evidence-based decision-making. While the literature has paid limited attention to tail-risk assessment in the CEE context, this paper extends the framework into an area that is methodologically feasible and policy-relevant.

Growth-at-Risk provides a flexible and theoretically grounded framework for signaling recession risk and economic turning points. Furno and Giannone (2024) offer an important theoretical link between GaR and classical binary EWS, showing that while GaR relies on the inverse cumulative distribution function, EWS rely on the cumulative distribution function, revealing a structural mirroring between the two approaches. This insight strengthened our objective of reinterpreting GaR as a direct and probabilistic EWS. Unlike traditional classification models like logit or probit, GaR captures asymmetries and tail risks through skewed-t distributions and quantile regressions. While machine learning models handle non-linearities, their opacity and data demand limit policy use. GaR combines theoretical structure with flexibility, making it well-suited for macro-financial forecasting and policy analysis.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature, focusing on the role of financial indicators, the developments of Macro-at-Risk literature and the evolution of EWS Section 3 provides an overview of the dataset. Section 4 outlines the methodological framework, presenting the proposed GaR-based EWS approach and the evaluation strategy used to benchmark its performance against a traditional logit model. Section 5 discusses the empirical findings, highlighting that the GaR-based EWS performs comparably to the classical model. Finally, Section 6 concludes by summarizing the main results and discussing their implications for forward-looking policymaking.

2. Literature review

In contemporary literature, three main directions have been identified as particularly important for this research. The first is related to financial conditions, should they still be considered as early warning indicators? The second research direction is related to Macro-at-Risk innovations. The third line of research explores alternative models for recession probabilities.

The first direction studies the predictive ability of financial conditions. The yield curve has been a cornerstone of early warning systems since the seminal work of Estrella and Hardouvelis (1989). They argued that a change in the shape of the yield curve reflects the expectations of financial market participants about the economy. Since then, sustained inversions of the yield curve have been regarded as an early signal for upcoming recessions. However, the global economy and financial markets have continued to evolve ever since. There have been several economic and financial crises. Sometimes financial conditions have been able to anticipate them ahead of time by at least a few months. The Great Financial Crisis is an example. In the United States, the NFCI indicator (calculated by the Chicago Federal Reserve) indicated a period of stress beginning in August 2007, before the banking system began to fail. Recession officially started in December 2007 (according to NBER).

However, since the Great Financial Crisis, in many economies the yield curve has not returned to its classic upward-sloping shape. As a result, EWS have indicated persistently higher recession probabilities. Recent studies suggest that quantitative easing (QE) programs by central banks have played a significant role in this shift by compressing long-term government bond yields. Gräb, Titzck (2020) explore the effects of different QE programs on short-term and long-term yields for USA. They propose adjustments for the Fed's, ECB's, and other major central banks QE programs. Sabes and Sahuc (2022) further validate these findings, noting a decline in the yield curve's predictive performance for the euro area in recent decades. Eser et al. (2023) examines the impact of asset purchase programs, highlighting their significant effects on the 10-year yields. More recent research, including Fonseca et al. (2023) and Bussiere and Lhuissiere (2024), confirms that adjustments to the yield curve are necessary to maintain predictive accuracy. Despite these challenges, financial conditions remain essential as early warning indicators. But data analysis is required to refine their predictive capabilities.

Ultimately, the term spread serves as an indicator of investor sentiment, but only among participants in the sovereign fixed income market. Consequently, the literature has advanced by incorporating explanatory variables into models designed to provide early warnings of economic cycle reversals, variables that reflect investor sentiment across other markets as well. These include, for instance, equity returns or volatility in equity markets, and corporate bond spreads in corporate fixed income markets. Fornari and Lemke (2010) validate the dominant predictive power of the yield curve inversion but reveal through their proposed ProbVAR model that forecasting performance can be improved by incorporating additional factors that reflect financial conditions, specifically, equity returns, corporate bond spreads, and short-term interest rates. These components are captured by the CLIFS index. Giglio et al. (2015) find that volatility indicators, particularly those linked to equity markets, are even more informative about future real economic downturns than non-volatility measures, as they better capture downside risk in a quantile regression-based analysis. Borio et al. (2019) draw a clear distinction between the advantages and limitations of the yield curve. While they acknowledge the widespread popularity of the yield curve as a predictive tool, they demonstrate, based on out-of-sample evidence, that other indicators more closely linked to the financial cycle, such as credit dynamics, can provide additional information and exhibit improved performance, particularly over the long term. In their empirical exercise, Borio et al. (2019) find that the term spread lacks statistically significant predictive power, whereas a composite indicator including the credit-to-GDP gap and the debt-service ratio shows statistically significant effectiveness. Vrontos et al. (2021) developed machine learning models to predict U.S. recessions, employing variables such as equity prices, money supply measures, interest rates, and credit market indicators, instead of just using the yield curve information.

The literature on composite financial indicators has emerged from the need for parsimonious measures that aggregate market sentiment. As noted by Copaciu (2022), the ECB's Country-Level Index of Financial Stress (CLIFS) effectively captures stress across the three main financial markets, equity, fixed income, and foreign exchange. CLIFS also accounts for co-movements among these markets, enabling a comprehensive assessment of systemic risk. These qualities motivated our choice of CLIFS as a proxy for financial conditions.

Our paper contributes to this literature by updating the findings regarding the predictive ability of financial conditions, with a particular focus on the Central Eastern European region, where studies on this theme remain scarce. While advanced financial conditions indices such as the GSFCI - Hatzius and Stehn (2018) and the NFCI - Brave and Butters (2011) are well established for the United States, and indicators like the CLIFS, CISS, and the Banque de France Financial Conditions Index - Petronevich and Sahuc (2019) are available for the euro area, the CEE region remains relatively underserved. Currently, only the Country-Level Index of Financial Stress is accessible for CEE countries, and only a limited number of studies have constructed dedicated financial conditions indices or examined their empirical relevance in relation to economic developments in the region. Ho and Lu (2013) construct FCIs for Poland using PCA and weighted averages, showing superior GDP growth forecasting versus standard leading indicators. Auer (2017) develops a sophisticated Dynamic Factor Model-based FCI for Hungary, Poland, and the Czech Republic, incorporating regional spillovers and demonstrating strong predictive power for GDP. Ganchev and Paskaleva (2021) extend this to eleven CEE countries, using PCA on multiple financial variables to create an FCI that effectively signals recession risks. Collectively, these studies highlight the growing importance of FCIs for understanding financial and economic dynamics in the CEE region.

The IMF's Growth-at-Risk guide, Prasad et al. (2019), emphasizes that tail risks should be assessed from multiple perspectives, not solely through financial market stress. While typically intensifies near economic downturns, long-term risks are more often driven by structural factors, termed macro-financial vulnerabilities by the IMF. Prasad et al. (2019) underscore the importance of both financial conditions and macro-financial indicators in capturing these longer-term vulnerabilities. Their study identifies key macro-financial imbalances, such as credit-to-GDP gaps, housing market distortions, and external imbalances including current account deficits, external flows, debt, and financing needs, as critical drivers of systemic risk. Validating Prasad et al. (2019) arguments, Galán (2020) explicitly argues that financial conditions, as captured by the CLIFS index, are not sufficient on their own and should be complemented by indicators of macro-financial vulnerabilities, which demonstrate stronger predictive performance. While CLIFS shows a significant and negative impact on the 5th quantile of GDP growth at a one-year horizon, indicators such as the credit-to-GDP gap, or the current account balance exhibit a significant impact at the same horizon and a stronger influence on GDP tail-risk at both one- and three-year horizons.

The necessity of macro-financial vulnerability indicators is also emphasized in the study by Lang et al. (2023). The authors argue that while indicators related to spreads and market volatility, as well as those reflecting the financial cycle, perform well at a one-year horizon, only financial cycle proxies provide clear signals regarding medium- to long-term Growth-at-Risk. In their analysis, they employ the Systemic Risk Indicator (SRI) developed by Lang et al. (2019), which incorporates information on the current account-to-GDP ratio and the dynamics of key variables such as the credit-to-GDP ratio, real total credit, debt-service ratio, residential real estate prices, and real equity prices. Their estimates reveal a "rich term-structure of Growth-at-Risk," as Lang et al. (2023) note, characterized by a short-term decline in tail risk but an accumulation of risk over the medium to long term.

Given the evolving challenges in interpreting financial conditions and more frequent uncertain economic times, there has been a growing recognition of the need for more advanced and comprehensive tools to assess macroeconomic risks. This has led to the emergence of Macro-at-Risk (MaR) literature, representing the second significant direction.

One of the earliest contributions to MaR was the development of structural tools for assessing tail risks. While Growth-at-Risk initially emerged as an empirical time series model, it soon became integrated into structural modelling. Adrian et al. (2019) revisited the theme of the dual mandate of central banks, balancing inflation targeting with financial stability. The authors proposed a New-Keynesian model that introduces the concept of real GDP Gap-at-Risk. Adrian et al. (2019) demonstrate that integrating a risk measure into the monetary policy reaction function leads to welfare gains. Later, Adrian et al. (2020) extended this approach by proposing the New-Keynesian Vulnerability Model (NKV).

Another growing area focuses on adapting GaR for macroprudential policy assessment. Pioneering work by Franta and Gambacorta (2020) and Suarez (2022) laid the foundation, followed by more recent studies such as Škrinjarić (2024). Today, GaR is widely used by macroprudential authorities for policy assessments.

Researchers also examine the structural factors influencing variations in GaR, such as Gachter et al. (2023), who analyse country-level differences, and Emter et al. (2024), who investigate the role of institutional quality in monetary policy's impact on GaR.

On the technical side, MaR research has seen extensions through Bayesian inference and ML. Bayesian estimates, first introduced by Szabo (2020), map the conditional distribution to official projections or surveys of professional forecasters, offering more stable and consistent results for short datasets. Additionally, advancements in machine learning have further tried to enhance GaR's predictive power. Yanchev (2022) discusses the use of artificial neural networks to improve GaR's conditional distribution modelling, while Kipriyanov (2022) finds that quantile random forests offer predictive abilities comparable to classical quantile regression.

In summary, the MaR field has expanded significantly. While Growth-at-Risk has been widely applied to assess downside risks, its potential as a direct early warning system for recessions remains underexplored. Although early warning models and GaR share conceptual similarities, most studies treat them as distinct approaches rather than as complementary frameworks. Recent research has begun to investigate these linkages, but an empirical evaluation of GaR's ability to directly estimate recession probabilities is still missing. Our paper seeks to bridge this gap by adapting GaR into an early warning framework and assessing its predictive performance relative to traditional binary models.

While the first two literature directions look at financial conditions' prediction performance and at Macro-at-Risk developments, the third direction takes a different approach: estimating recession probabilities through classification models. The most prominent methodologies in this area have been logistic and probit regression models, but recent advancements have led to a shift toward more complex techniques, such as machine learning (ML) algorithms. It is important to note that there is no consensus on the superiority of machine learning. While these models may offer a more reliable approach in complex environments, where classical models are prone to instability, they do not consistently outperform traditional models in simpler scenarios. Moreover, the rapid proliferation of machine learning models across disciplines has led to concerns about a research bias toward these techniques. Navarro et al. (2021) identified three common issues in assessing machine learning performance in clinical studies: inadequate handling of missing data, overfitting, and small sample sizes.

Turning back to economics, James (2018) concludes that the SVM model is an effective method for predicting US recessions. Its performance is comparable to that of the Dynamic Factor Models and Learning Vector Quantization Model. However, his study is limited to the U.S., and the forecasting horizons differ due to varying data frequencies. Consequently, a direct comparison between the models is less feasible. Holopainen and Sarlin (2016) demonstrate that ensemble learning algorithms outperform traditional Probit when aggregating advanced techniques. In contrast, Puglia's (2020) work provides a comprehensive analysis of the ML algorithms performance, including Random Forest, XGBoost, LightGBM, Neural Network, and Support-Vector Machine. The author employs macroeconomic and financial market data. The results demonstrate that ML models do not exhibit superior performance compared to probit models, after cross-validation. Nevertheless, Puglia (2020) still recommends incorporating machine learning algorithms into practitioners' toolkits for their ability to capture non-linearities. Psimopoulos (2020) also explored recession prediction using machine learning algorithms, Logit, and Probit regressions for six countries, but found no clear consensus. The results did not demonstrate that logit and probit outperformed, nor were they outperformed by machine learning algorithms. For all countries, at least one machine learning model outperformed the classical models, but not all of them. Our study integrates well into this third direction by proposing Growth-at-Risk as a complementary early warning model. GaR should be seen as a bridge between the advantages of classical and modern methods. We demonstrate that GaR performs at least as well as traditional tools in predicting recession probabilities.

A recent contribution by Furno and Giannone (2024) offers initial insights into the theoretical link between early warning modelling of recession probabilities and Growth-at-Risk. In the paper, a nowcasting system for a "technical" recession (defined as two consecutive quarters of negative GDP growth) is formulated. The methodology follows a Bayesian logistic regression with flat priors. Although the paper does not directly establish a statistical link between Growth-at-Risk and logit-based recession probabilities through empirical modelling or correlation analysis, the authors provide a theoretical foundation for such a link. Furno and Giannone (2024) observe that the distinction between EWS and GaR is merely a matter of perspective. EWS use a linking function to a CDF, while Growth-at-Risk relies on the inverse distribution function. The theoretical foundation of this paper has reinforced our conviction in the soundness of our presented advantages and empirical results. Indeed, our paper represents a practical extension of the study conducted by Furno and Giannone (2024). We take a step further and estimate recession probabilities directly through Growth-at-Risk.

3. Data

The analysis includes eleven economies from the Central Eastern European region, namely: Austria, Bulgaria, the Czech Republic, Croatia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia, and Slovenia. The estimation sample spans from 2005 to 2024. Quarterly frequency is used. The early warning capacity of financial conditions through Growth-at-Risk-based classification model was analysed for eight horizons, from one to eight quarters. These forecast range captures both the near-term forecasting and the medium-term forecasting performances.

It is widely acknowledged that there is no universally accepted formula for identifying an economic recession. Simplified methods, like the Hodrick-Prescott filter, often align with more complex models but have limitations, such as end-point bias. Multivariate models are more accurate but can be complex. The "technical recession" definition, two consecutive quarters of negative GDP growth, is widely used. It is used even by Furno and Giannone (2024), but can be misleading, as seen during the pandemic's sharp decline and rebound. Recession identification is subjective, with each method having its drawbacks.

Our study does not focus on dating business cycles. Instead, we employ transparent methodology to identify recessionary periods for the selected economies. We employed the annual real GDP gaps estimated by the European Commission. For each country, these estimates are based on the methodology of McMorrow et al. (2014), which relies on a production function. We converted the real GDP gap to quarterly frequency using the Chow-Lin method with average as disaggregation method. Industrial production was used as the linking variable, chosen for simplicity and its broad recognition as a reliable proxy for GDP. Episodes of negative values for the GDP gap are designated as recessionary periods.

Two sets of regressors have been used. For estimates covering all selected CEE economies, we rely exclusively on GDP gap persistence and the Country-Level Index of Financial Stress (CLIFS), estimated by the European Central Bank. The CLIFS indicator is accessible for all European Union members, and it is a commonly employed metric for financial condition. We opt for a composite index over the yield curve, as it captures a broader range of financial market indicators and provides a more comprehensive measure of financial conditions.

Duprey and Ueberfeldt (2020) emphasize the importance of financial stress, measured by the country-level index of financial stress (CLIFS) proposed by Duprey et al. (2017), as a key short-term driver of downside GDP risk. Copaciu (2022) highlights the advantages of CLIFS, noting that its incorporation of co-movements across equity, bond, and foreign exchange markets enhances its ability to capture systemic financial stress episodes, similar with the methodology of Hollo et al. (2012). Copaciu (2022) reveals larger impacts of macroeconomic shocks under the presence of high-level of financial stress, expressed by CLFIS.

For the second type of estimates, the multivariate analysis incorporates variables that are either specific to emerging economies or grounded in theory, such as real monetary conditions. The selection strategy follows the recent literature that emphasizes the complementary role of short-term financial conditions and longer-term macro-financial vulnerabilities in assessing recession risk. In this regard, we include variables from three broad categories: financial stress indicators, domestic vulnerabilities, monetary conditions (credit gap, real interest rate gap), and external imbalances (current account deficit, net international investment position dynamics). The GDP gap persistence is replaced by the Economic Sentiment Indicator (ESI), which remains strongly correlated with the gap while offering better leading properties. This structure enables us to capture both cyclical pressures and structural fragilities that jointly shape downside risks in emerging markets. Since economic activity is usually analysed by means of an IS curve, real monetary conditions have been introduced, through the real interest rate and the real exchange rate. Real monetary conditions were expressed in gaps from trend, obtained through the HP filter. In addition to real monetary conditions, agents' expectations were integrated through the Economic Sentiment Indicator. As a pioneering contribution to real-time recession warning systems for the euro area, Camacho et al. (2010) incorporate the ESI alongside other high-frequency hard and soft indicators. They argue that the ESI offers a structured, quantifiable signal based on qualitative survey data from professionals. Tkacova and Gavurova (2023) show that the ESI offer solid predictive power for economic cycles in several EU countries, particularly after 2008. Very important for our study are Dewachter et al. (2023) findings. Their study suggests that the ESI not only predicts expected GDP growth but also signals downside risks in the euro area. Lower ESI values are linked to broader, left-skewed GDP growth distributions, indicating heightened recession risk.

Ever since the Great Financial Crisis, macro-financial linkages have been considered and the literature searched for the highly informative variables in the medium term about vulnerabilities. As already mentioned in the literature, the common variables are related to the credit cycle, external imbalances, and excessive financial flows.

According to Jordà et al. (2013), credit expansion during economic booms significantly increases a country's vulnerability, underscoring the cyclical role played by financial factors. In line with the empirical evidence presented by Jordà et al. (2013), prior to the development of the Growth-at-Risk framework, Aikman et al. (2019) also highlight the importance of macro-financial vulnerability indicators. They argue that credit booms, still present around periods of severe GDP contractions, serve as effective signals of medium-term tail risks. Furthermore, over a three-year horizon, the dynamics of house prices and current account deficits may also indicate rising vulnerabilities. Similarly, Arbatli-Saxegaard (2020), in a study focused on Norway and a panel of advanced economies, examines the distribution of medium-term GDP growth and identifies credit growth as the most relevant early warning indicator of tail-risk.

Considering the findings from the literature, the existence of feedback loops between the economy and the banking system has been widely acknowledged and discussed. In this respect, we used the credit deviation as predictor. Initially, the credit cycle was estimated following the BIS recommendation. We used the Hodrick-Prescott One-Sided filter with a λ coefficient value of 400,000 for the credit to GDP ratio. But, as noted by Grecu and Cheptis (2024), financial cycles in the CEE region appear to be shorter than those observed in advanced economies. While the BIS recommends a λ of 400,000, Grecu and Cheptis (2024) ultimately adopted the standard quarterly value of 1,600 for the CEE region. In our analysis, we tested multiple values to determine the most informative specification. Indeed, our results indicate that a lower λ provides a more meaningful representation of financial fluctuations. Accordingly, we apply the Hodrick-Prescott One-Sided filter with λ 1,600 to extract the credit gap.

Since emerging economies struggled with persistently elevated levels of imbalances and the current account deficit was recognised in literature as a risk factor, we considered appropriate to introduce the current account deficit as a ratio of GDP.

The selected countries have benefited over the last two decades from episodes of high financial in-flows. In the literature there have been concerns about the Net International Investment Position or about the fluctuations in foreign direct investments. In this regard, we assume that such flows may have a favourable effect, but up to a point in the long run. We introduce as a predictor the net international investment position dynamic (as % of GDP). Eguren-Martin et al. (2024) contribute to the Macro-at-Risk literature by emphasizing the importance of monitoring financial flows. They highlight that periods of intense in-flows and outflows can create pressures on the financial system, with large outflows identified as particularly disruptive to economic stability.

In the next paragraphs descriptive analysis is presented for the core variables, financial conditions the primary predictor and for the dependent variable, the real GDP gap.

Most economies studied from the Central Eastern European region have closed their GDP gaps in the long run, achieving equilibrium. The mean and median values are zero. The gap closing may be a signal that countries have reached a proper level of convergence and stabilisation over the last two decades. But the statistical amplitude remains high. There is a strong asymmetry between the magnitudes of business cycles. If the maximum magnitude of GDP deviation from potential is about 18% for the expansionary cycle (for Slovakia), for the recessionary cycle the maximum deviation (for Romania) is about 27%. This still suggests an elevated level of vulnerability for these countries that have been under a developing process. Distributions are defined by fat tails, kurtosis revealing a leptokurtic form. Also, the distribution is asymmetric. The mass of the distribution is rather positive. Thus, the GDP deviation does not follow a normal distribution. Central and Eastern Europe shows high volatility, with some countries avoiding overheating, like Austria and Hungary. Poland managed peaks and troughs despite not maintaining a near-zero gap. Bulgaria is remarkable by the stable and low cycles. Of major importance is the aspect of a well-balanced dataset for our binary variable. More than 50% of the sample represents recessionary cycles, a feature that allows us to have high confidence in assessing performance through AUROC. The evolution of the GDP gaps provided by AMECO can be consulted in Appendix, Figure A1. The heatmap reveals a high degree of cycle synchronization across CEE countries, with all economies gaining negative GDP gaps during 2009–2010 and again around 2020. However, the depth and timing of downturns vary. Latvia, Lithuania, Hungary show faster extreme gaps, while Poland and Bulgaria exhibit milder contractions. Romania has a lagging recession deepening and Slovenia started to have lower than 6 percent GDP gaps only starting with 2012. Post-2019 patterns show divergence, highlighting emerging heterogeneity in recovery dynamics, However, most of the economies seem to have negative GDP gaps.

Table 1: Descriptive statistics for GDP gaps and financial conditions

	Real GDP gap	Financial Conditions (CLIFS)
Mean	–0.01	0.13
Median	–0.06	0.09
Maximum	17.86	0.85
Minimum	–27.53	0.02
Std. Dev.	3.89	0.10
Skewness	–0.40	2.37
Kurtosis	7.34	11.15
Jarque-Bera test	713.77	3259.25
Probability	0	0
Negative GDP gap share	50.57%	

Source: Eurostat database, author's calculations

Financial conditions often show common spikes, reflecting contagion effects. The CLIFS indicator spiked during global shocks, such as the Great Financial Crisis (GFC), the COVID-19 pandemic outbreak, and the Russia-Ukraine conflict. This is visible in Table 1, looking at the significant positive value of skewness and the prominent level of excess kurtosis. Financial conditions show an asymmetric leptokurtic distribution for the CEE region. Austria and Bulgaria had a delayed response to the GFC in terms of financial stress but saw sustained stress afterward. Evolution of the CLIFS indicator can be consulted in the Appendix, Figure A2.

The CLIFS indicator fulfills order zero integration. GDP gaps exhibit stationarity similar to CLIFS. All the statistical tests show consensus with a high confidence level. The same results are obtained in the case of the real exchange rate gap, real interest rate gap, economic sentiment indicator and for the credit-to-gdp gap. Divergence between tests is obtained for the NIIP dynamics and in terms of current account balance, only tests with intercept signal stationarity. Overall, the stationarity properties of the variables do not raise major concerns regarding their use in the empirical models. Stationarity tests considering common unit root, but also individual unit root are available in the Appendix in tables A1-A8.

4. Methodology

This section presents the transformation of Growth-at-Risk into an early warning system. The procedure consists of three main steps. First, conditional quantiles are estimated using quantile regression, with financial conditions and other macroeconomic predictors serving as explanatory variables. These quantiles capture the asymmetric risks associated with economic downturns. Next, to ensure coherence and eliminate quantile crossing issues, a Skewed-T distribution is fitted to the estimated quantiles, smoothing the conditional distribution, and providing a more robust risk assessment. Finally, instead of using the inverse cumulative distribution function (CDF), as in standard GaR applications, we shift to the direct CDF to compute the probability that GDP growth falls below zero. This adjustment allows GaR to function as a classification model for recession prediction, aligning it with early warning system frameworks. The following paragraphs provide a detailed description of each step.

To estimate the probability of a negative real GDP gap at a given future time, first we follow the traditional GaR approach.

We estimated the quantile regressions, which holds the following form:

$$\hat{Q}_{\left(y_{i,\,t+h}\,|x_{i,t}\right)}\left(\tau\ |x_{i,t}\right) = \hat{\alpha}_{h,\tau} + \hat{\delta}_{h,\tau} y_{i,\,t} + x_{i,t}'\,\hat{\beta}_{h,\tau} \tag{1}$$

where $y_{i,t+h}$ represents the real GDP gap of country i, h quarters ahead; $\boldsymbol{x'}_{i,t}$ represents a vector of financial indicators, financial conditions (simplified configuration) or financial conditions and a set of macro-financial vulnerabilities indicators, both measured at time t, for country i; h = 1, 2, ..., 8 quarters; τ = 0.05, 0.25, 0.75, 0.95; $\hat{\beta}_{h,\tau}$ denotes the vector of quantile-specific slope coefficients associated with the predictors $\boldsymbol{x'}_{i,t}$, estimated separately for each forecast horizon h and quantile level τ.

Following Adrian et al. (2019), we estimate four quantiles, the 5th, 25th, 75th, and 95th, which are symmetrically distributed around the centre of the conditional distribution. This selection provides sufficient flexibility to capture both tail behaviour and the shape of the distribution around the median, without introducing instability in the parametric fitting. The Skewed-T distribution employed in the GaR literature is defined by four parameters that determine its location, scale, skewness, and kurtosis. Estimating these parameters requires at least four quantiles that are well distributed across the support of the data. The 5th and 95th quantiles provide crucial information about downside and upside tail risks, while the 25th and 75th quantiles describe the intermediate mass of the distribution and help ensure accurate curvature. While including the median could offer additional insight into central tendency, our focus is primarily on risk in the distribution tails and turning points, which makes the selected quantiles most relevant for our early warning application. Including more quantiles is theoretically possible but may complicate the fitting process if estimated coefficients in quantile functions violate monotonicity, especially in small samples. This issue becomes even more pronounced in multivariate settings, where quantile regression estimates are particularly sensitive to model dimensionality and sample size. In Appendix, figure A5, we illustrate the estimated quantile processes for two models (with 4 and 8 lags), showing that coefficient instability can emerge even in a simplified setup that includes only output gap persistence and financial conditions. The instability becomes especially evident in the 8-lag specification, reinforcing the need for a parsimonious quantile structure.

Based on the selected quantiles, the four parameters distribution can be estimated. The last two, which govern skewness and kurtosis, offer a flexible structure for modelling the full conditional distribution of the GDP gap. Unlike standard normal or symmetric distributions, the Skewed-T allows for control over location, scale, skewness, and tail heaviness, making it well-suited to capture asymmetries and fat tails. This flexibility becomes particularly valuable when modelling downside risks, as the distribution can adjust dynamically to reflect periods of heightened uncertainty or financial distress. Compared to classical models such as logit or probit, which assume symmetry and impose a fixed functional form, the Skewed-T framework enables the conditional cumulative distribution to better adapt to real-world data. This is especially relevant when financial conditions amplify lower-tail risks in a non-linear manner.

For the quantile regression, proposed by Koenker and Bassett (1978), the coefficients estimation represents a generalisation of the OLS method. The optimisation problem requires minimising the weighted sum of absolute deviations, with weights determined by a quantile loss function which accounts for the asymmetry of the quantile.

$$\hat{\alpha}_{h,t},\, \hat{\delta}_{h,t},\, \hat{\boldsymbol{\beta}}_{h,t} = \arg\min \sum\nolimits_{i,t} \rho_\tau \left[y_{i,t+h} - (\hat{\alpha}_{h,t} + \hat{\delta}_{h,t}\gamma_{i,t} + \hat{\beta}_{h,t}) \right] \tag{2}$$

Quantile regression is a minimisation problem for each specified quantile. However, relying solely on quantile regression estimates to map a probability distribution function can be unreliable because of errors and noise. The main challenge in describing the entire distribution is ensuring the no-crossing quantiles condition. To address this issue, Adrian, Boyarchenko, and Giannone (2019) proposed the use of the parametric Skewed-T distribution, developed by Azzalini and Capitanio (2003). Smoothing the quantile estimates by fitting the Skewed-T distribution gives the parameters for the following probability density function:

$$\mathrm{f}(y,\, \mu,\, \sigma,\, \alpha,\, \upsilon) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};\, \upsilon\right) T\left(\alpha\, \frac{y-\mu}{\sigma} \sqrt{\frac{\nu+1}{\nu + \frac{y-\mu}{\sigma}}};\, \upsilon+1\right) \tag{3}$$

Fitting the mentioned parametric distribution requires the minimisation of the squared distance between the quantile estimates and the parametric quantile functions.

$$\hat{u}_{i,t+h},\, \hat{\sigma}_{i,t+h},\, \hat{\alpha}_{i,t+h},\, \hat{v}_{i,t+h} = \underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{\mathrm{Q}}_{\left(y_{i,\,t+h} \mid\, x_{i,t}\right)} \left(\tau \mid \boldsymbol{x}_{i,t}\right) - \mathrm{F}^{-1}\left(\tau;\, \mu,\sigma,\alpha,\nu\right) \right)^2 \tag{4}$$

However, for the Skewed-T distribution, neither the CDF nor its inverse (the quantile function) has a closed-form expression due to the distribution's flexibility in accommodating both skewness and heavy tails (kurtosis). As a result, the inverse CDF is computed numerically.

The optimisation problem comprises four unknown parameters (μ, σ, α, ν) and four quantile regression functions, resulting in an exactly identified system. Nelder-Mead numerical algorithm was used for solving the problem. The Nelder-Mead is a derivative-free optimization method suited for problems where the objective function is non-linear, and gradients are unavailable or difficult to compute. The algorithm iteratively explores the parameter space by evaluating function values. Importantly, the estimation is performed under constraints (positivity of scale and tail thickness parameters) to ensure numerical stability.

Our final objective is to transform the Growth-at-Risk into a classification model that can effectively early warn an impending recession. This ensures alignment with the conventional approach. After completing the two steps of Growth-at-Risk, a probability density function, $f\left(y, \hat{\mu}, \hat{\sigma}, \hat{\alpha}, \hat{\upsilon}\right)$, is obtained. Leveraging the principles of probability theory, the cumulative distribution function (CDF) can then be derived by integrating the PDF. This integration is done over the range of values up to a specified point and is obtained through numerical algorithms.

$$F\left(y\right)=P\left(Y\leq y\right)=\int_{-\infty}^{y} f\left(t\right)dt \tag{5}$$

For a direct EWS for recessions, our goal is to ascertain the probability that the GDP gap will exhibit values lower than zero. Once this target is defined, the following CDF is obtained:

$$F\left(0 \mid \hat{\mu}_{i,t+h}, \hat{\sigma}_{i,t+h}, \hat{\alpha}_{i,t+h}, \hat{v}_{i,t+h}\right)=\int_{-\infty}^{0} f(y \mid \hat{\mu}_{i,t+h}, \hat{\sigma}_{i,t+h}, \hat{\alpha}_{i,t+h}, \hat{v}_{i,t+h})dy \tag{6}$$

As we have said, our extension does not move far apart from GaR. It is just a change of perspective. Indeed, our approach mirrors Growth-at-Risk. While Adrian, Boyarchenko, Giannone (2019) used the inverse distribution function to ascertain the tail values, we are capturing the likelihood of negative real GDP gap, obtaining the CDF numerically.

Subsequently, the efficacy of the newly implemented early warning model should be evaluated. We considered as a benchmark the logistic regression. For interpreting classification efficiency, we used the commonly employed performance measure AUROC. As the datasets were well equilibrated, AUROC measure was feasible. It was imperative for us to establish an analysis framework to ensure the impartiality of our study, and the integrity of the results obtained. The differences in AUROC values between GaR and Logit were evaluated, through statistical significance tests. First, performance was assessed on panel estimates including all countries and only GDP gap persistence and CLIFS as predictors. Then the performance was assessed on the multivariate panel estimates for the non-EEA CEE countries.

Quantile regression, particularly at the tails of the distribution, is known to require large sample sizes to produce stable and reliable estimates, as highlighted by Chernozhukov and Fernández-Val (2011). The paper indicates a rule of thumb whereby, for example, estimating the 5th quantile with five covariates would require at least 1,500 observations to ensure high confidence in parameter stability. Given that our empirical framework includes extreme quantiles (the 5th and the 95th), the sample size at the individual country level would be insufficient to guarantee robust estimation, raising the risk of coefficient instability and violations of the monotonicity condition across quantiles. Such issues would likely undermine the second step of the Growth-at-Risk procedure, namely, the fitting of the parametric distribution, by causing convergence difficulties and reducing model credibility.

For these reasons, we adopted a pooled panel quantile regression approach, which increases the effective sample size and facilitates more stable parameter estimation across quantiles. This setup allows us to examine macro-financial linkages at the regional level while preserving the comparability of Growth-at-Risk and logit models across different configurations. Admittedly, pooling comes at the cost of not explicitly accounting for cross-country heterogeneity. While logistic regression can accommodate heterogeneity through fixed effects, quantile regression models with fixed effects remain methodologically more complex and are subject to potential biases unless advanced estimators, such as those proposed by Koenker (2004), Canay (2011), or Powell (2022), are used. Fixed effects with different methodologies between models were considered a barrier for our performance assessment.

Accordingly, we recognize the lack of heterogeneity control as a limitation in our analysis. Nonetheless, for the primary purpose of comparing the performance of alternative EWS, the use of pooled quantile regression provides a pragmatic and statistically justifiable solution.

The adequacy of the Skewed-T distribution is validated by the convergence of empirical quantiles towards the theoretical quantiles, incorporating asymmetry and heavy tails. This behaviour can be observed through the evolution of the distribution's specific parameters, $\hat{\alpha}$ and $\hat{\upsilon}$, estimated from the panel dataset. These two parameters are shown both for estimates covering the full sample of countries across all eight forecast horizons and for the subsample with multivariate configuration. Figures A3-A4 in Appendix depict the min, max, and average values of $\hat{\alpha}$ and $\hat{\upsilon}$ across countries over time. The shifts in $\hat{\alpha}$ and $\hat{\upsilon}$ capture periods of heightened risk. It is particularly noticeable that during periods of macro-financial stress, such as the 2008–2010 interval, the parameter $\hat{\alpha}$ becomes significantly negative in most cases. This clearly indicates a longer left tail of the distribution, precisely matching theoretical expectations. Regarding kurtosis, although in simplified models at short forecast horizons the $\hat{\upsilon}$ parameter reaches high values for a significant part of the sample (suggesting a possible absence of excess kurtosis), for longer horizons, where uncertainty typically increases, the $\hat{\upsilon}$ parameter predominantly decreases. This strongly indicates a platykurtic shape of the fitted distributions.

5. Empirical Results

The results are presented in four main sections. First, we discuss the results for the simplified EWS, which use only financial conditions and GDP gap persistence as predictors. In the second sub-section, we present univariate panel quantile regression estimates (25th quantile) for the non-Euro Area CEE countries. The 25th quantile was chosen over the 5th quantile to ensure greater robustness. Both capture the lower tail of the conditional distribution, making a directional difference unlikely. However, the 25th quantile provides more reliable estimates. Even with a panel dataset, the 5th quantile lacks sufficient observations to meet the minimum threshold recommended by Chernozhukov and Fernández-Val (2011). Based on these univariate estimates we have selected the early-warning indicators used in the multivariate setting. The third sub-section focus on the multivariate model for the non-EA CEE countries. The last section illustrates estimated individual recession probabilities.

5.1 Simplified early-warning models (GaR vs Logit)

The results at various horizons indicate a strong short-to-medium-term early warning capacity for a recession. This outcome holds regardless of the methodology used, whether Macro-at-Risk or logistic regression. For a horizon of up to one semester, AUROC performance even exceeds 90%. In this context, financial conditions and the persistence of the GDP gap enable an effective distinction between recessionary and expansionary. Over a three-quarter period, the AUROC value remains above 80%, suggesting a strong early warning capacity. However, economic state forecasts for horizons of one year or one year and one quarter show values ranging between 70% and 80%, reflecting satisfactory but insufficient performance. Over longer periods, the model based on financial conditions and GDP gap persistence fails to adequately signal recessions, with the AUROC value falling below the heuristic threshold of 70%. A key conclusion is that financial conditions even in emerging economies serve as reliable and effective early-warning indicator for cycle reversals.

Table 2: AUROC values for estimates using CLIFS and GDP gap persistence

Model\Horizon	GaR-EWM	Logit-EWM	AUROC diff. (GaR-Logit)
1 quarter	94.58%	94.43%	0.15 p.p.
2 quarters	90.97%	90.69%	0.28 p.p.
3 quarters	85.37%	84.98%	0.39 p.p.
4 quarters	78.54%	78%	0.54 p.p.
5 quarters	73.34%	72.75%	0.59 p.p.
6 quarters	68.63%	68.70%	-0.07 p.p.
7 quarters	65.46%	65.81%	-0.35 p.p.
8 quarters	64.54%	65.30%	-0.76 p.p.
Average			0.10 p.p.

Notes: p.p. means percentage points
Source: author’s calculations

Differences in model performance indicate that the Growth-at-Risk (GaR) model performs better up to a five-quarter horizon. However, for forecast intervals ranging from one and a half to two years, logistic regression has the advantage. That said, the average difference in AUROC is minimal, amounting to just 0.1 percentage points in favour of the GaR model. In all cases, performance differences remain within one percentage point.

Statistical significance tests confirm that there are no substantial differences in performance. Both the mean and median of the AUROC differences are not significantly different from zero. This indicates that using MaR does not lead to performance trade-offs.

Table 3: Significance tests for AUROC differences

	Mean	Median		
		Sign (normal)	Wilcoxon signed rank	van der Waerden (normal scores)
t-statistic	0.58	0.35	0.63	0.54
Probability	57.78%	72.00%	52.00%	58.00%

Source: author's calculations

5.2 Multivariate early-warning models (GaR vs Logit)

Multivariate MaR goes beyond serving as an alternative benchmark evaluation. It improves performance evaluation and identifies other early warning indicators, uncovering new insights. A multivariate approach can outperform financial-conditions model, making it a more effective early-warning tool. A preliminary overview of variable impacts is available in Table 4.

The Economic Sentiment Indicator, developed by the European Commission, captures agents' expectations and has a statistically significant impact on the lower part of the distribution. Positive expectations contribute notably, even up to eight quarters ahead. However, this impact gradually diminishes as the two-year horizon approaches. Nonetheless, a decline in expectations signals risks for the economy, extending into the medium to long term.

Real monetary conditions do not appear to have a medium-to-long-term impact on GDP gap risk. If they do influence the central tendency in the medium term, their effect may be overshadowed by other indicators with stronger early-warning capabilities for risks. In the medium to long term, monetary policy should not be a major concern in Central and Eastern Europe, as central banks can achieve their objectives without causing significant risks.

Up to one semester real monetary conditions have a significant impact. While a rise in the real interest rate increases risks, a real appreciation of the national currency is more likely to indicate an improvement. This evidence suggests that the financial and wealth channels are stronger than the trade channel. Due to the euroization effect and the high level of foreign currency debt, exchange rate appreciation has a stronger positive effect on disposable income than its negative impact on price competitiveness. This finding aligns with existing literature, as noted by Kearns and Patel (2016) and Banerjee et al. (2022) for the emerging economies.

Financial conditions play a crucial role in driving risk and, consequently, the probability of a recession. In the short run, their impact increases slightly as the influence of agents' expectations diminishes. However, in the medium term, the coefficient on financial conditions declines and eventually becomes statistically insignificant at the two-year horizon. These findings validate the short to medium-term evidence from the Growth-at-Risk literature. As identified by Adrian, Boyarchenko, and Giannone (2019), the lower tail of conditional distributions is largely explained by the level of financial stress. This decline in predictive power suggests that financial markets react swiftly to changing conditions, making short-term signals more reliable, while long-term economic risks may depend more on structural factors such as external imbalances or external financial flows.

The credit cycle has a risk-mitigating effect, highlighting the importance of bank funding in Central and Eastern Europe and the need to maintain financial stability to prevent credit shortages. An expanding credit cycle leads to a reduction in economic activity risks, even in the medium term, though the effect gradually diminishes. No peak was identified to indicate possible long-term negative effects of a boom-bust credit cycle.

The current account balance does not have a significant impact on risk. Non-linear specifications of the equation have been tested in this case as well, but no substantial effects were identified. However, in the very short term, just one quarter, a statistically significant negative coefficient emerges. This suggests that a current account deficit is associated with a reduction in risk. While this relationship may seem intuitive, it contrasts with the typical impact of net exports on GDP. But in periods of favourable economic conditions, higher disposable income leads to increased consumption of goods and services. As a result, rising income levels naturally contribute to a widening trade imbalance through higher imports.

Probably the most important finding regarding early warning indicators is the significant role of financial flows. Changes in the net international investment position (NIIP) strongly influence long-term risk. Negative changes (net in-flows) reflect rising risks. From a policy perspective, these findings suggest that excessive reliance on foreign in-flows could heighten economic vulnerability. Policymakers should closely monitor NIIP dynamics. In this context, exuberant economic imbalances, such as external or fiscal deficits, may become tempting but should be avoided. While external financing may be accommodative in the short term, over-reliance on foreign in-flows in the long run could lead to disruptive financing shortages, increasing vulnerability to economic shocks and instability. The estimates reveal a quadratic relationship with a minimum point. This relationship suggests that for declines of more than approximately 10 percentage points in NIIP, risk is slightly attenuated. For extreme values of net financial in-flows, such as 30-35%, risks are even replaced by positive contributions to the 25th conditional quantile of the GDP gap. This relationship might suggest a compensating effect of the short-term benefits of external financing on long-term risks. But a 30% NIIP decrease is abnormal, as the minimum change was 22.6%, observed in Bulgaria in 2008. Therefore, even the existence of this polynomial relationship does not change the message: external financing is beneficial, but with limits, especially in the presence of macroeconomic imbalances. Intensive reliance on external flows leads to long-run vulnerabilities.

Table 4: Univariate results for the 25th conditional quantile for non-EA dataset

	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
ESI	0.21*** (15.99)	0.120*** (15.84)	0.19*** (15.87)	0.18*** (13.85)	0.15*** (7.37)	0.11*** (4.40)	0.06*** (3.28)	0.04** (2.45)
Real Interest Rate Gap	−0.13* (−1.86)	−0.12** (−1.96)	−0.08 (−1.43)	−0.04 (−0.63)	0.06 (0.75)	0.12 (1.39)	0.15 (1.34)	0.14 (1.16)
Real Exchange Rate Gap	−0.26*** (−3.63)	−0.16* (−1.89)	−0.06 (−0.69)	0.05 (0.79)	0.06 (0.93)	0.07 (1.01)	0.06 (0.75)	0.08 (0.93)
Financial Conditions	−6.62*** (−4.60)	−8.19*** (−5.66)	−9.034*** (−6.84)	−8.27*** (−7.52)	−7.23*** (−4.30)	−6.36*** (−4.27)	−5.17*** (−3.53)	−4.40 (−4.32)
Credit Gap	0.21*** (4.16)	0.20*** (5.19)	0.20*** (4.97)	0.19*** (4.45)	0.16*** (2.90)	0.11** (2.20)	0.08*** (2.40)	0.07*** (3.24)
Current account deficit	−0.11* (−1.71)	−0.04 (−0.84)	−0.01 (−0.27)	0.02 (0.55)	0.06 (1.22)	0.09* (1.67)	0.14** (2.24)	0.13** (2.22)
Dynamics of NIIP	−0.004 (−0.10)	0.00 (0.03)	0.02 (0.45)	0.03 (1.05)	0.05* (1.77)	0.07*** (2.97)	0.08*** (3.42)	0.09*** (3.71)
Squared Dynamics of NIIP	0.001 (0.35)	0.00 (0.12)	0.002 (0.51)	0.003 (1.24)	0.003 (1.30)	0.004** (2.12)	0.004* (1.86)	0.006*** (3.09)

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%. Values in brackets represent t-statistics values. Standard errors estimated based on bootstrap method x-y pairs with 25000 iterations.

Source: author’s calculations

For the non-EA countries in the CEE region, the multivariate estimates differ from the results of the simplified model applied to the broader region. AUROC values for the short horizons are noticeably lower, reflecting the higher volatility and uncertainty of business cycles, which stem from the ongoing convergence process. At a horizon of just one quarter, AUROC values start at 84%. However, unlike the simplified configuration, which includes only the CLFIS and the gap persistence, AUROC values for these countries remain above the 70% threshold even at 8 quarters. This suggests that more complex models are desirable for medium- to long-term forecasting. This is intuitive, as rising financial stress is more likely to signal concerns about immediate economic challenges, not about long-term issues. The decline in performance is gradual and AUROC values remain close to 80% up to the one-year horizon.

Table 5: AUROC values for multivariate estimates

Model\Horizon	GaR-EWM	Logit-EWM	AUROC diff. (GaR-Logit)
1 quarter	83.20%	84.10%	−0.90 p.p.
2 quarters	83.00%	83.10%	−0.10 p.p.
3 quarters	81.03%	81.10%	−0.07 p.p.
4 quarters	78.70%	79.06%	−0.36 p.p.
5 quarters	76.50%	76.50%	0.00 p.p.
6 quarters	73.83%	74.40%	−0.57 p.p.
7 quarters	72.41%	72.46%	−0.05 p.p.
8 quarters	71.30%	71.19%	0.11 p.p.
Average			−0.24 p.p.

Notes: p.p. means percentage points
Source: author's calculations

As in the simplified setup, performance differences remain within 1 percentage point in terms of AUROC. However, in contrast to the previous results, the logistic regression model performs slightly better. Only for the 8-quarter horizon, GaR-EWM outperforms the logistic regression model, while for the 5-quarter interval, their performance is the same. The average performance difference is -0.24 percentage points.

The statistical significance tests show stronger evidence in this case. Though, the tests do not show a consensus regarding significant performance differences. Only the test for the mean and van der Waerden (normal scores) median test show a small level of significance. As a result, we cannot confirm the superiority of the logistic regression compared to our Growth-at-Risk-based model. Instead, also considering the previous results, it could be said that GaR-Early Warning model is suitable for practical use and recession prediction.

Table 6: Significance tests for AUROC differences

	Mean	Median		
		Sign (normal)	Wilcoxon signed rank	van der Waerden (normal scores)
t–statistic	–1.99	1.51	1.6	–1.68
Probability	8.60%	13.06%	10.83%	9.20%

Source: author's calculations

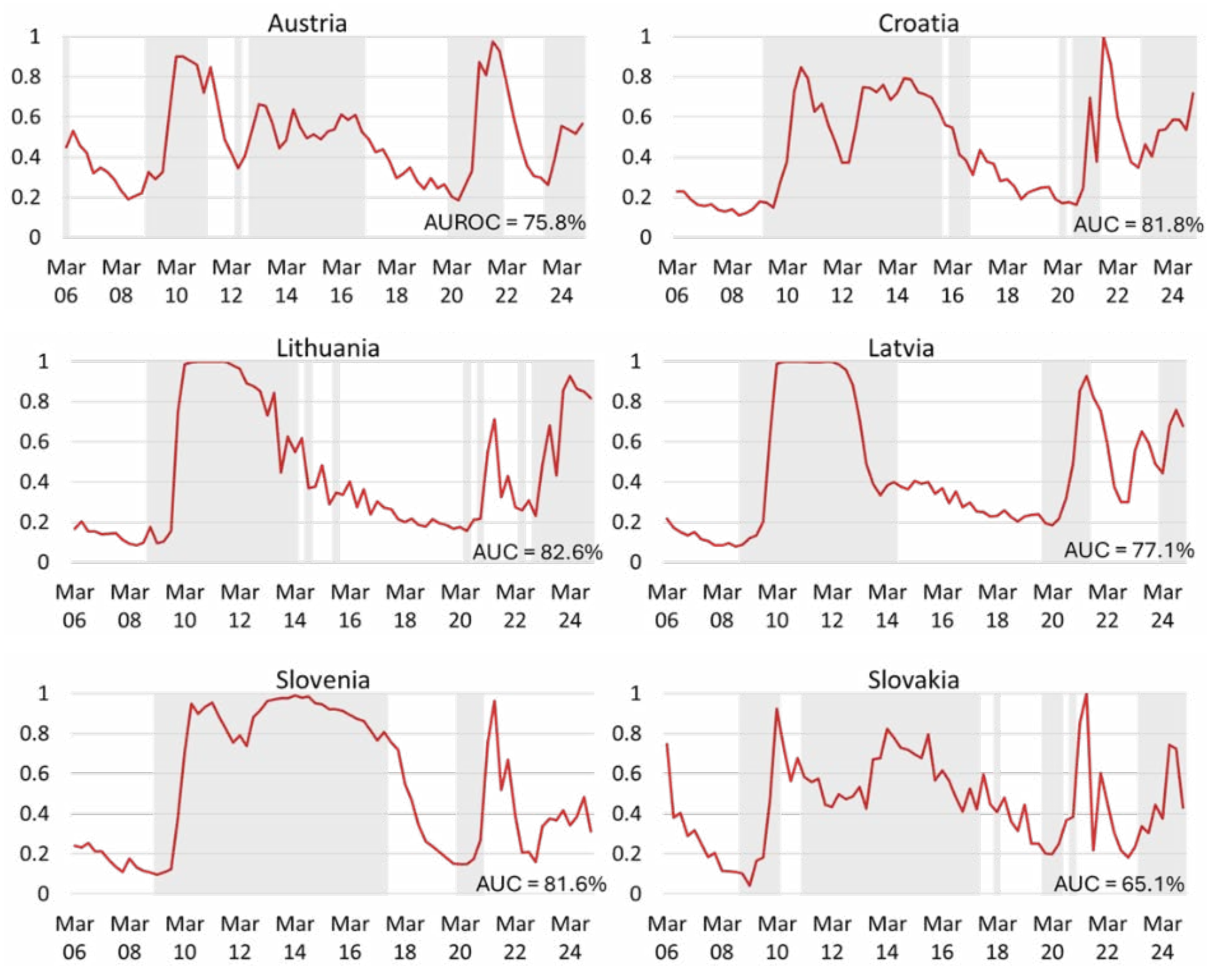
5.3 Country-level recession probabilities

In the figures that follow, we present the recession probabilities generated by our GaR-based models for the most policy relevant forecast horizons. We begin with the one-year horizon, first on the simplified specification and then on the non-euro-area subsample specification. Because the five-country multivariate model did not deliver clear improvements at this horizon, we also present the two-year forecasts. This allows us to assess whether, as the literature suggests, adding macro-financial vulnerability indicators improves medium-to-long-run performance.

Across all panels, we observe strong synchronization in both business-cycle turning points and financial-conditions shocks. Every country registers a pronounced rise in recession probability during the Global Financial Crisis, lasting roughly from 2009 through 2015–2017. The COVID-19 shock also emerges clearly as a synchronized spike in every series. More recently, several countries, Slovakia, Latvia, Austria, Croatia, Poland, Romania, and Hungary, show rising recession probabilities beginning in 2023 and extending to the end of our sample.

At the one-year horizon, all models successfully flag the Great Financial Crisis, albeit with a lag of a few months. This performance, coupled with the model's timelier anticipation of the 2023 downturn, is illustrated in Figure 1. In this one-year window, uncertainty remains relatively low compared to longer horizons. Thus, this permits us to compare cross-country performances and identify possible strong heterogeneity. Accordingly, AUCs cluster around 80%, indicating a reasonable degree of homogeneity in macro-financial linkages across these CEE countries. Notably, for Slovakia the model underperforms relative to its peers, while Bulgaria's model shows both a markedly different and overall poor fit. This might suggest the necessity of excluding Bulgaria in future research.

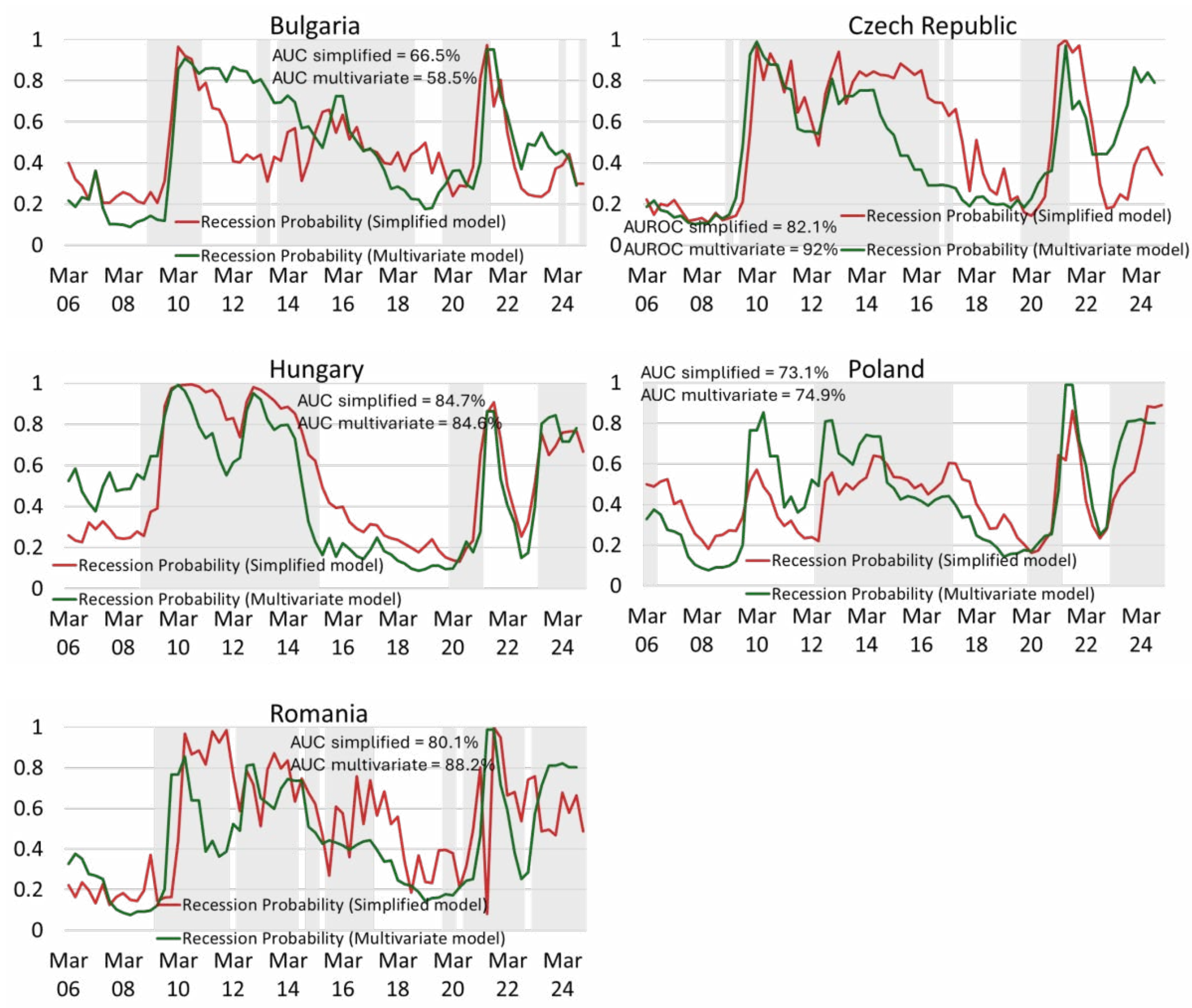
Figure 1: EA countries-recession probabilities, one year-ahead model



Note: shaded areas represent recessionary periods
Source: author's calculations

In all five countries for which we estimated the multivariate specification, the inclusion of macro-financial vulnerability indicators produced reasonable gains in performance. In the Czech Republic, the AUC even rises above 90%. For Bulgaria and Romania strong improvements are noticed. Just for Poland and Hungary the improvements are marginal. These patterns are illustrated in Figure 2, which compares the one-year-ahead recession probabilities derived from the simplified and multivariate models.

Figure 2: Non-EA countries-recession probabilities, one year-ahead model

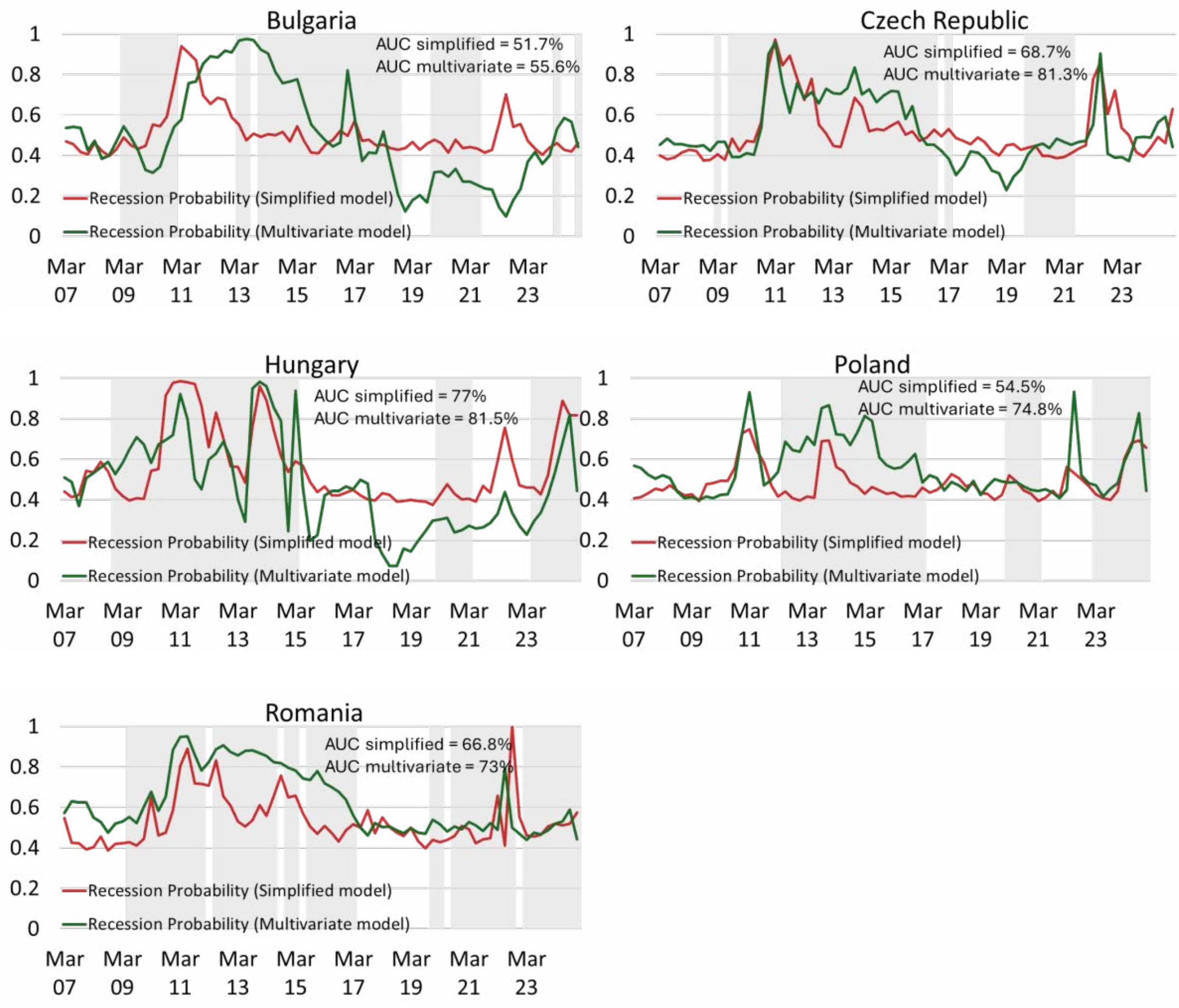


Note: shaded areas represent recessionary periods

Source: author's calculations

For the two-year forecast horizon, incorporating macroeconomic imbalances, external financial flow dynamics, and the financial cycle, alongside standard financial conditions substantially improve performance in all cases. Figure 3 illustrates these results, with AUC gains recorded in each case. Poland, in particular, shows a notable increase in predictive performance, with the AUC rising by as much as 20 percentage points.

Figure 3: Non-EA countries-recession probabilities, two year-ahead model



Source: author's calculations

Thus, our results are consistent with the literature suggesting that, in the longer term, macro-financial vulnerability indicators may play a more significant predictive role, compared to financial conditions indicators, which typically amplify rapidly only close to extreme events.

6. Concluding Remarks

We proposed an extension of the GaR methodology, adapting it into an EWS. This technical adaptation offers a novel classification tool, underpinned by strong theoretical foundations.

The results are mixed. While in the simplified setting, the GaR model slightly outperforms Logit, the opposite holds true in the multivariate setting for non-EA countries.

Given these blended outcomes regarding performance differences, it is not possible to declare one model as systematically superior. Instead, the findings suggest that both models have their strengths depending on the context. Policymakers should consider incorporating the extended Growth-at-Risk model when addressing cycle reversals. Achieving higher performance for a specific horizon with GaR, alongside its inherent advantages, could enhance the forecasting and policy analysis toolkit for practitioners. As central banks begin adopting Growth-at-Risk frameworks, it would be a missed opportunity not to leverage the methodology also as a direct early warning system.

The research methodology was straightforward, closely following the framework of Adrian, Boyarchenko, and Giannone (2019). We focused on just four symmetric conditional quantiles. By expanding the number of quantiles, it may be possible to incorporate additional information into the conditional distribution, drawn from financial conditions or other early-warning indicators. Additionally, symmetric quantiles may not always be the optimal choice for distribution fitting. The decision regarding the number and selection of quantiles rests with the user. Fine-tuning these parameters could enhance the accuracy.

We suggest the following stepwise procedure for quantile selection. Start by estimating the model using the 0.05, 0.25, 0.75, and 0.95 quantiles, as outlined in Adrian, Boyarchenko, and Giannone (2019). In the second step, additional quantiles can be introduced incrementally, beginning with the 0.5 (median), followed by the 0.1 and 0.9 quantiles. The median is particularly important for capturing the central tendency of the distribution. The 0.1 quantile can provide valuable insights into recession probabilities, which typically reside in the left tail during normal economic conditions, while the 0.9 quantile helps to better understand the right tail. If the inclusion of additional quantiles improves the results, they should be retained; otherwise, they can be excluded systematically. Alternatively, practitioners may consider analysing sensitivity-specificity curves to identify abrupt changes in performance across quantiles and incorporate those that enhance the model's predictive power.

As a further research direction, we propose studying the application of Growth-at-Risk as an early warning system for the "technical recession" definition. Specifically, Growth-at-Risk could be employed to estimate the probabilities of two consecutive quarters of negative growth, as demonstrated by Furno and Giannone (2024) that used a Bayesian logit model. However, the classical GaR model is not suitable for this purpose. Instead, the methodology should transition from a univariate Skewed-T distribution to a multivariate framework, utilising Skewed-T Copula functions. While the general methodology remains unchanged, this adaptation is necessary because consecutive growth rates are not independent, making joint probability estimation more complex.

The key advantage of the GaR approach lies in its ability to yield a flexible distribution, setting it apart from classical models. When resources are available to carefully select an optimal set of quantiles, Growth-at-Risk as an early warning model has the potential to deliver even superior practical results. By reversing the Growth-at-Risk procedure from inverse CDF to CDF, practitioners can extract additional insights from the same foundational methodology.

Our paper provides evidence for the Central and Eastern European (CEE) region that financial conditions contain valuable information for predicting recessions. Based on panel multivariate estimates it is advisable to integrate also other leading indicators. Evidence suggests that emerging economies from the CEE should be aware of the double-edged importance of external financial in-flows. Even though they are beneficial, excessive in-flows might suggest pro-cyclical movements ending with a cycle reversal in the long-run. Additionally, survey-based sentiment indicators could provide forward-looking guidance substituting the real GDP gap persistence which has only a role in the short run. Credit flows can sustain economic activity and reduce risks.

As central banks increasingly adopt Growth-at-Risk, integrating it as a direct early warning system represents a natural extension. Doing so could enhance policymakers' ability to anticipate economic downturns and proactively adjust macroeconomic policies, contributing to financial and economic stability.

A limitation of the present approach lies in the use of the Nelder–Mead optimisation algorithm for fitting the parametric Skewed-T distribution. While this derivative-free search method is well suited for low-dimensional, smooth, and well-behaved objective functions, as in our panel setting, it is known to be sensitive to local minima and does not guarantee convergence to the global optimum. In our empirical implementation, convergence was consistently achieved, likely due to the simplicity of the model structure and the statistical robustness of the estimated quantiles. Nonetheless, for applications involving more complex specifications or shorter time series (country-level analyses instead of panel analysis), optimisation robustness might be a concern. Future research may consider employing gradient-based methods such as the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. Additionally, in our case we did not face severe heterogeneities, except for Bulgaria, which the results suggest is an outlier. But, for GaR-based EWS models with extended structural factors (specific for labour market, international trade, economy's structure) a higher degree of heterogeneity control would be desirable.

References

Adrian, T., Boyarchenko, N., Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4), 1263–1289. https://doi.org/10.1257/aer.20161923

Adrian, T., Duarte, F., Grinberg, F., Mancini-Griffoli, T. (2019). *Monetary Policy and Financial Conditions: A Cross-Country Study*. FRBNY. Staff Reports No. 890. https://www.newyorkfed.org/research/staff_reports/sr890

Adrian, T., Duarte, F., Liang, N., Zabczyk, P. (2020). NKV: A New Keynesian Model with Vulnerability. *AEA Papers and Proceedings*, 110, 470–476. https://doi.org/10.1257/pandp.20201023

Adrian, T., Grinberg, F., Liang, N., Malik, S., Yu, J. (2022). The term structure of Growth-at-Risk. *American Economic Journal: Macroeconomics*, 14(3), 283–323. https://doi.org/10.1257/mac.20180428

Aikman, D., Bridges, J., Hacioglu Hoke, S., O'Neill, C., Raja, A. (2019). *Credit, capital and crises: a GDP-at-Risk approach*. Bank of England Working Paper No. 824. https://www.bankofengland.co.uk/working-paper/2019/credit-capital-and-crises-a-gdp-at-risk-approach

Arbatli-Saxegaard, E. C., Juelsrud, R. E. (2020). *Countercyclical capital requirement reductions, state dependence and macroeconomic outcomes*. Norges Bank WP 2020/9. https://www.norges-bank.no/en/news-events/publications/Working-Papers/2020/92020/

Auer, S. (2017*). A Financial Conditions Index for the CEE Economies*. Bank of Italy Temi di Discussione No. 1145. https://www.bancaditalia.it/pubblicazioni/temi-discussione/2017/2017-1145/index.html?com.dotmarketing.htmlpage.language=1&dotcache=refresh

Azzalini, A., Capitanio, A. (2003). Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 65(2), 367–389. https://doi.org/10.1111/1467-9868.00391

Banerjee, R., Hofmann, B., Mehrotra, A. (2022). Corporate investment and the exchange rate: The financial channel. *International Finance*, 25(3), 296–312. https://doi.org/10.1111/infi.12415

Borio, C. E. V., Drehmann, M., Xia, F. D. (2019). *Predicting Recessions: Financial Cycle versus Term Spread*. BIS Working Paper No. 818. https://www.bis.org/publ/work818.htm

Bussiere, M., Lhuissier, S. (2024). What does an inversion of the yield curve tell us?. Banque de France. *Bulletin de la Banque de France*, 250(3). https://www.banque-france.fr/en/publications-and-statistics/publications/what-does-inversion-yield-curve-tell-us

Brave, S., Butters, R. A. (2011). Monitoring financial stability: A financial conditions index approach. *Economic Perspectives, 35*(Q I), 22–43. https://ssrn.com/abstract=1758783

Camacho, M., & Pérez-Quiros, G. (2010). Introducing the euro-sting: Short-term indicator of euro area growth. *Journal of Applied Econometrics, 25*. https://doi.org/10.1002/jae.1174

Copaciu, A. M., Horobet, A. (2022). Spillovers in the presence of financial stress – an application to Romania. *Journal for Economic Forecasting, 0*(2), 29–43. https://ideas.repec.org/a/rjr/romjef/vy2022i2p29-43.html.

Chernozhukov, V., Fernández-Val, I. (2011). Inference for Extremal Conditional Quantile Models with Application to Market and Birthweight Risks. *Review of Economic Studies*, 78(2), 559–589. https://doi.org/10.48550/arXiv.0912.5013

Dewachter, H., Báča, P., Beeckman, W. (2023). *The ESIs: A finger on the pulse of the European economy?* KBC Institute Research Report. https://www.kbc.com/en/economics/publications/the-esis-a-finger-on-the-pulse-of-the-european-economy.html

Duprey, T., Klaus, B., Peltonen, T. (2017). Dating systemic financial stress episodes in the EU countries. *Journal of Financial Stability, 32*, 30–56. https://doi.org/10.1016/j.jfs.2017.07.004

Duprey, T., Ueberfeldt, A. (2020). *Managing GDP tail risk*. Bank of Canada. Staff WP 20-3. https://www.bankofcanada.ca/wp-content/uploads/2020/01/swp2020-3.pdf

Eguren-Martin, F., O'Neill, C., Sokol, A., von dem Berge, L. (2024). Capital flows-at-risk: Push, pull and the role of policy. *Journal of International Money and Finance*, 147(C). https://doi.org/10.1016/j.jimonfin.2024.103146

Emter, L., Moura, A., Setzer, R., Zorell, N. (2024). *Monetary Policy and Growth-at-Risk: The Role of Institutional Quality*. European Central Bank. ECB Working Paper No. 2989. https://www.bportugal.pt/sites/default/files/documents/2024-10/WP202414.pdf

Eser, F., Lemke, W., Nyhom, K., Radde S., Vladu, A.L. (2023). Tracing the impact of the ECB's asset purchase program on the yield curve, *International Journal of Central Banking*, 19(3), 359-422. Available at https://ideas.repec.org/a/ijc/ijcjou/y2023q3a9.html

Estrella, A., Hardouvelis, G. A. (1989). *The term structure as a predictor of real economic activity*. Federal Reserve Bank of New York. FRBNY Working Papers No 7.

Ferrari Minesso, M., Lebastard, L., Le Mezo, H. (2023). Text-based recession probabilities. *IMF Economic Review*, 71, 415–438. https://doi.org/10.1057/s41308-022-00177-5

Fonsenca, L., McQuade, P., Van Robays, I., Vladu, A.L. (2023). The inversion of the yield curve and its information content in the euro area and the United States. European Central Bank. *ECB Economic Bulletin 7/2023*, 42-46. Available at https://ideas.repec.org/a/ecb/ecbbox/202300072.html

Fornari, F., Lemke, W. (2010). *Predicting recession probabilities with financial variables over multiple horizons*. European Central Bank. ECB Working Paper No. 1255. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1255.pdf?17faf3181cddc6090d149d4c62a35f55

Franta, M., Gambacorta, L. (2020). On the effects of macroprudential policies on Growth-at-Risk. *Economics Letters*, 196, 109501. https://doi.org/10.1016/j.econlet.2020.109501

Furno, F., Giannone, D. (2024). Nowcasting Recession Risk. Research Methods and Applications on Macroeconomic Forecasting. Available at https://www.amazon.science/publications/nowcasting-recession-risk

Gächter, M., Geiger, M., Hasler, E. (2023). On the Structural Determinants of Growth-at-Risk. *International Journal of Central Banking*, 19(2), 251-293. Available at https://ideas.repec.org/a/ijc/ijcjou/y2023q2a5.html

Galán, J. (2020). *The benefits are at the tail: Uncovering the impact of macroprudential policy on Growth-At-Risk*. Banco de España. Banco de España Working Papers, WP No. 2007. https://doi.org/10.1016/j.jfs.2020.100831

Ganchev, T. G., Paskaleva, M. (2021). Financial condition indices and pandemic uncertainty as recession triggers. *Dos Algarves: Tourism, Hospitality & Management Journal, 39*, Article 7. https://doi.org/10.18089/DAMeJ.2021.39.7

Giglio, S., Kelly, B. T., Pruitt, S. (2015). *Systemic Risk and the Macroeconomy: An Empirical Evaluation*. Fama–Miller Working Paper, Chicago Booth Research Paper No. 12-49. https://doi.org/10.1016/j.jfineco.2016.01.010

Grab, J., Titzck, S. (2020). *US yield curve inversion and financial market signals of recession*. European Central Bank. ECB Economic Bulletins, 1/2020. https://www.ecb.europa.eu/press/economic-bulletin/focus/2020/html/ecb.ebbox202001_02~20b7c9a04e.en.html

Grecu, R.A., Cheptis, A. (2024). Synchronization of financial cycles in selected Central and Eastern European countries. *Journal of Eastern Europe Research in Business and Economics*, 2024(2024), 735542. https://doi.org/10.5171/2024.735542

Hamilton, J.D. (2018). Why you should never use the Hodrick-Prescott filter. The Review of Economics and Statistics, 100(5), pp.831–843. https://doi.org/10.1162/rest_a_00706

Hatzius, J., Stehn, S. J. (2018). *The case for a financial conditions index*. Global Economics Paper, Goldman Sachs Economic Research.

Ho, G., Lu, Y. (2013). *A Financial Conditions Index for Poland* (IMF Working Paper No. 252). International Monetary Fund. https://www.researchgate.net/publication/263529231_A_Financial_Conditions_Index_for_Poland

Hollo, D., Kremer, M., Lo Duca, M. (2012). *CISS – A composite indicator of systemic stress in the financial system*. European Central Bank. ECB Working Paper Series 1426. https://www.econstor.eu/bitstream/10419/153859/1/ecbwp1426.pdf

James, A., Abu-Mostafa, Y., Qiao, X. (2018). Machine learning for recession prediction and dynamic asset allocation. The Journal of Financial Data Science (forthcoming). http://dx.doi.org/10.3905/jfds.2019.1.007

Jarmulska, B. (2022). Random forest versus logit models: Which offers better early warning of fiscal stress?. *Journal of Forecasting*, 41(3), 455–490. https://doi.org/10.1002/for.2806

Jordà, Ò., Schularick, M., Taylor, A. M. (2013). When credit bites back. *Journal of Money, Credit and Banking, 45*(1), 3–28. https://doi.org/10.1111/jmcb.12069

Kearns, J., Patel, N. (2016). *Does the financial channel of exchange rates offset the trade channel?* BIS Quarterly Review, Bank for International Settlements, December. https://www.bis.org/publ/qtrpdf/r_qt1612i.htm

Kipriyanov, A. (2022). Comparison of Models for Growth-at-Risk Forecasting. *Russian Journal of Money and Finance*, 81(1), 23–45. https://doi.org/10.31477/rjmf.202201.23

Lang, J. H., Izzo, C., Fahr, S. A., Ruzicka, J. (2019). *Anticipating the bust: A new cyclical systemic risk indicator to assess the likelihood and severity of financial crises*. European Central Bank. ECB Occasional Paper Series 219. https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op219~7483083881.en.pdf

Lang, J. H., Rusnák, M., Greiwe, M. (2025). Medium-term Growth-at-Risk in the Euro Area. *IMF Economic Review*, 2025. https://doi.org/10.1057/s41308-024-00272-9

Liu, W., Moench, E. (2016). What predicts US recessions?. *International Journal of Forecasting*, 32(4), 1138–1150. https://doi.org/10.1016/j.ijforecast.2016.02.007

López-Salido, D. & Loria, F., 2024. Inflation at risk. *Journal of Monetary Economics*, 145(Supplement), 103570. https://doi.org/10.1016/j.jmoneco.2024.103570

Navarro C.L.A., Damen J.A.A., Takada T., S.W.J. Nijman, P. Dhiman, J. Ma, G.S. Collins, R. Bajpai, R.D. Riley, K.G.M. Moons, L. Hooft (2021). Risk of bias in studies on prediction models developed using supervised machine learning techniques: systematic review. *BMJ 375*. https://doi.org/10.1136/bmj.n2281

Petronevich, A., Sahuc, J.-G. (2019). A new Banque de France Financial Conditions Index for the euro area. *Banque de France Bulletin*, No. 223. https://publications.banque-france.fr/en/new-banque-de-france-financial-conditions-index-euro-area

Prasad, A., Elekdag, S. A., Jeasakul, P., Lafarguette, R., Alter, A., Feng, A. X., & Wang, C. (2019). *Growth at Risk: Concept and Application in IMF Country Surveillance*. International Monetary Fund. IMF Working Paper No. 2019/036. https://doi.org/10.5089/9781484397015.001

Psimopoulos, A. (2020). Forecasting economic recessions using machine learning: An empirical study in six countries. *South-Eastern Europe Journal of Economics*, 18(1), 40–99. https://www.asecu.gr/old_files/Seeje/issue34/issue34-psimopoulos.pdf

Puglia, M., Tucker, A. (2020). Machine learning, the treasury yield curve and recession forecast*ing*. *Finance and Economics Discussion Series* 38/2020. https://doi.org/10.17016/FEDS.2020.038

Sarlin, P., Holopainen, M. (2016). *Toward robust early-warning models: a horse race, ensembles and model uncertainty*. European Central Bank. ECB WP Series No. 1900. https://doi.org/10.48550/arXiv.1501.04682

Škrinjarić, T. (2024). *Growth-at-Risk for macroprudential policy stance assessment: a survey*. Bank of England. Bank of England Working Paper No 1075. https://www.bankofengland.co.uk/working-paper/2024/growth-at-risk-for-macroprudential-policy-stance-assessment-a-survey

Suarez, J. (2022). Growth-at-Risk and macroprudential policy design. *Journal of Financial Stability*, 60, 101008. https://doi.org/10.1016/j.jfs.2022.101008

Szabo, M. (2020). *Growth-at-Risk: Bayesian Approach*. Czech National Bank. Czech National Bank Working Papers No. 2020/3. https://www.cnb.cz/en/economic-research/research-publications/cnb-working-paper-series/Growth-at-Risk-Bayesian-Approach-00001

Tkacova, A., & Gavurova, B. (2023). Economic sentiment indicators and their prediction capabilities in business cycles of EU countries. *Oeconomia Copernicana, 14*(3), 977–1008. https://doi.org/10.24136/oc.2023.029

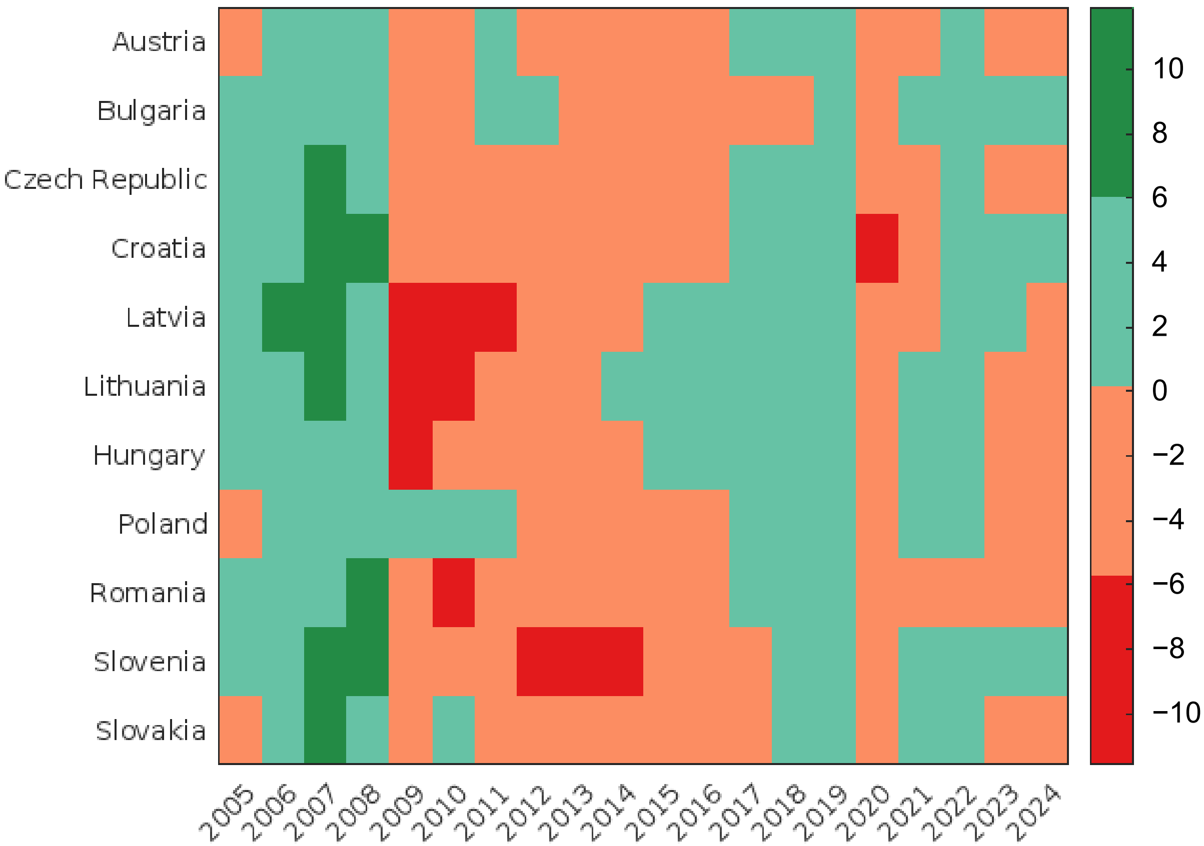
Vrontos, S. D., Galakis, J., & Vrontos, I. D. (2021). Modeling and predicting U.S. recessions using machine learning techniques. *International Journal of Forecasting, 37*(2), 647–671. https://doi.org/10.1016/j.ijforecast.2020.08.005

Yanchev, M. (2022). Deep Growth-at-Risk Model: Nowcasting the 2020 Pandemic Lockdown Recession in Small Open Economies. *Economic Studies Journal*, 7, 20–41. https://ideas.repec.org/a/bas/econst/y2022i7p20-41.html

Appendix

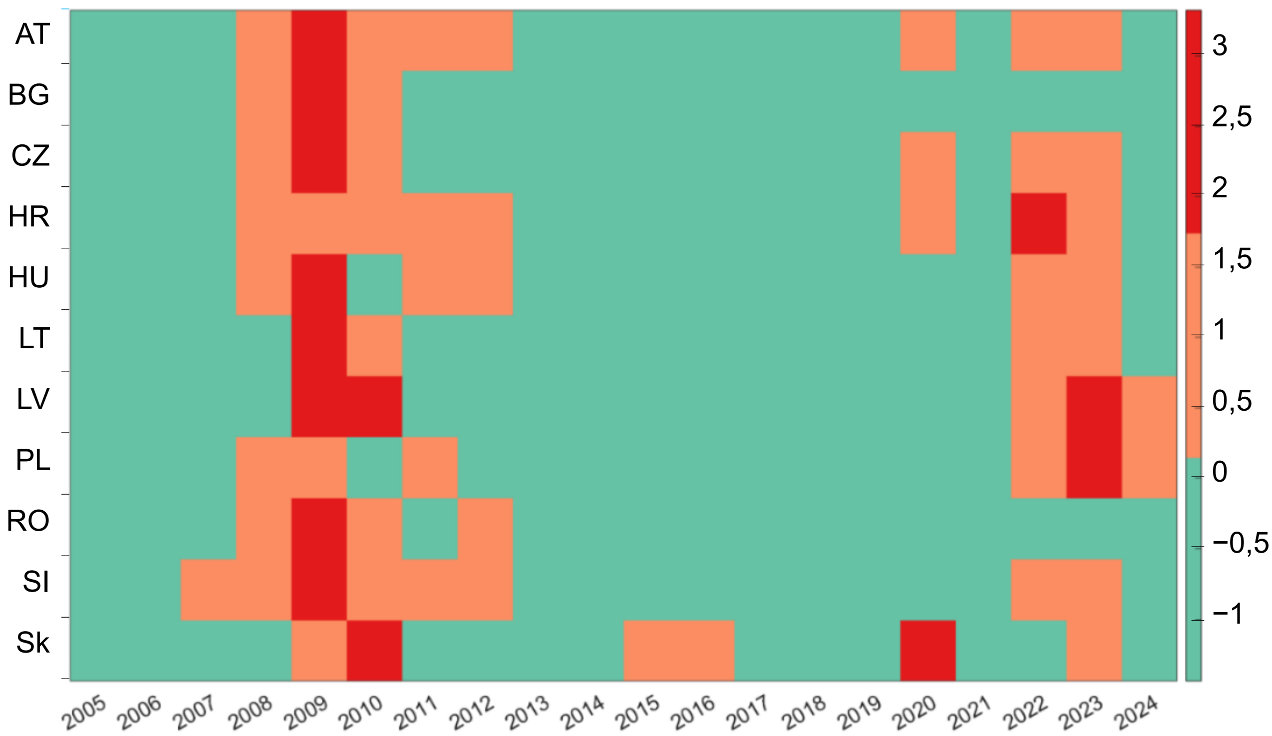
Descriptive analysis of core variables

Figure A1: GDP gap across countries and time (heatmap)



Source: Authors' processing, AMECO Database

Figure A2: CLIFS indicator across countries and time (annual standardised heatmap)



Source: Authors' processing, European Central Bank Database

Figure A3: Skewed-T parameters for simplified models

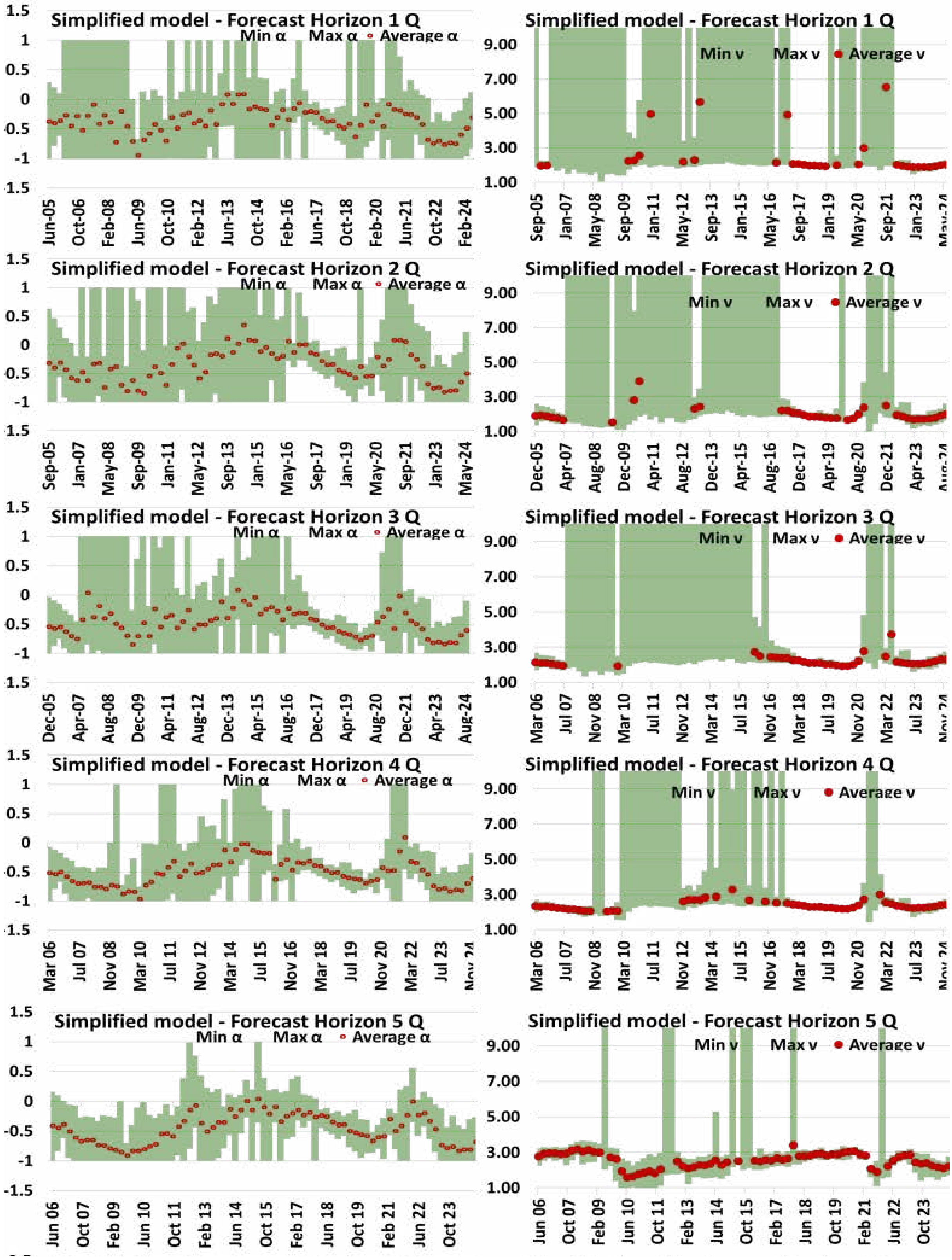
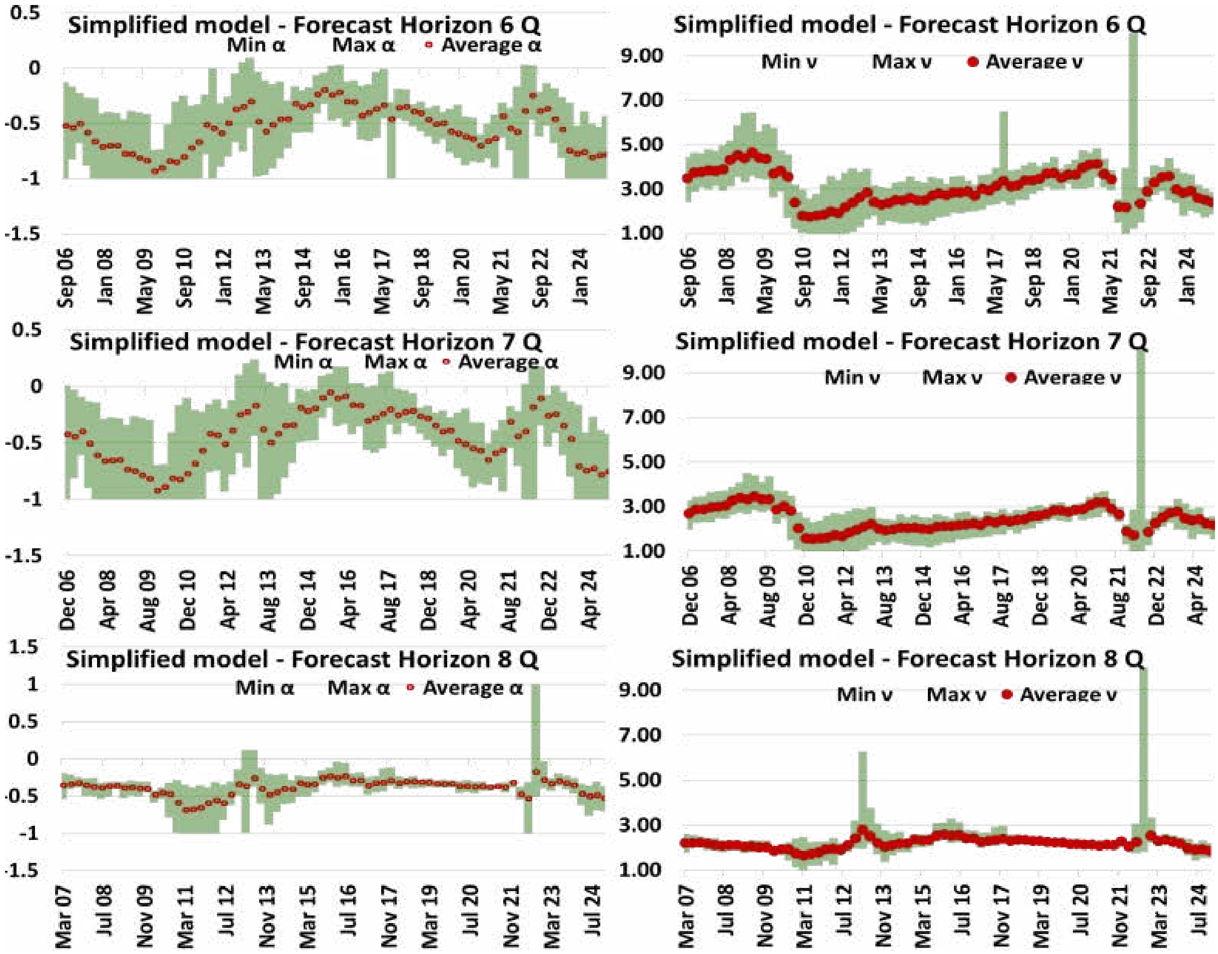


Figure A3: Continuation



Note: Min–max range (shaded) and mean (dots) of the Skewed-T parameters α (left) and ν (right), across all countries and forecast horizons. The evolution of α highlights left-tail fattening during crises, while movements in ν reflect changing kurtosis (tail thickness) over time.

Source: Author's processing

Figure A4: Skewed-T parameters for multivariate models

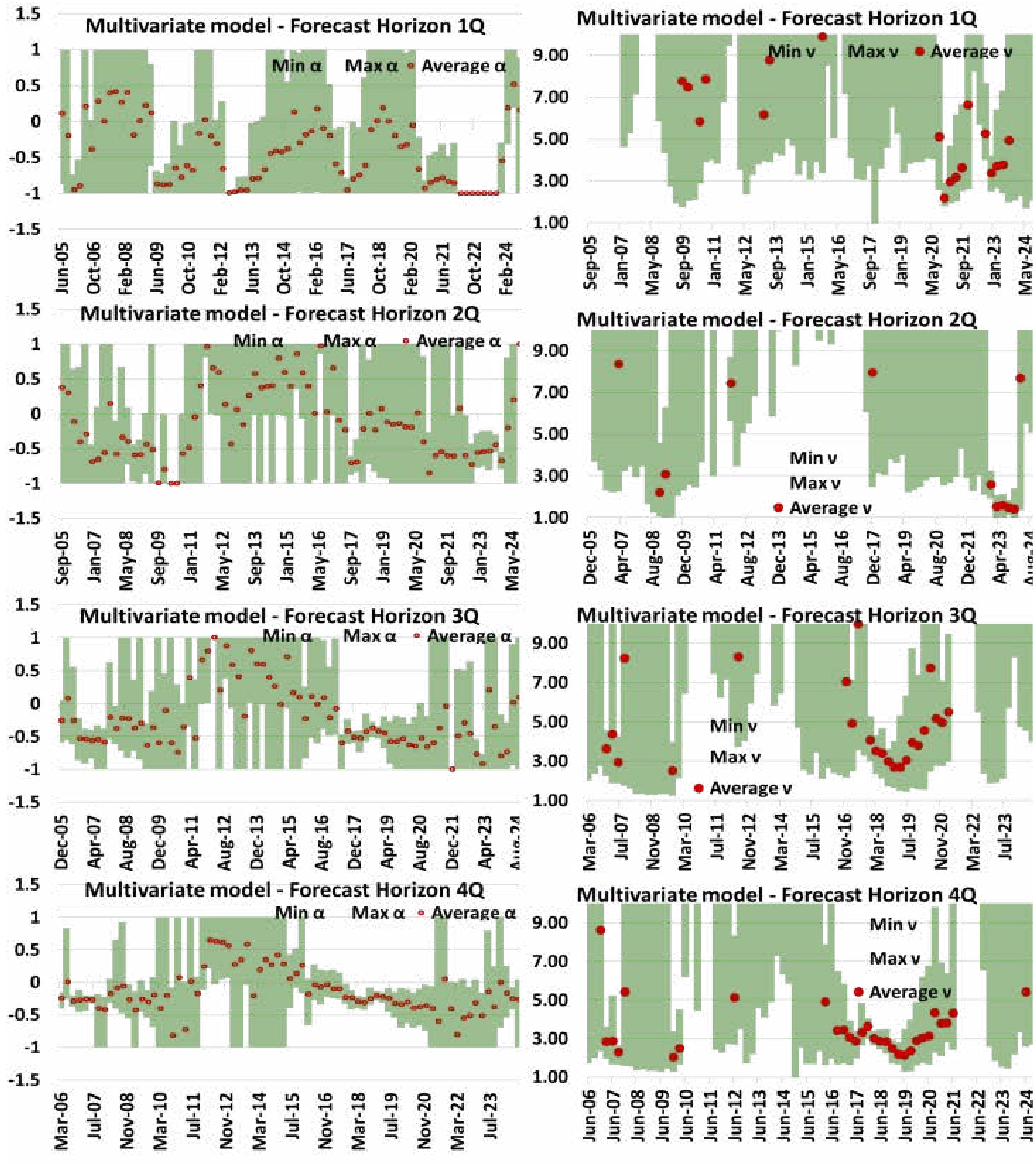
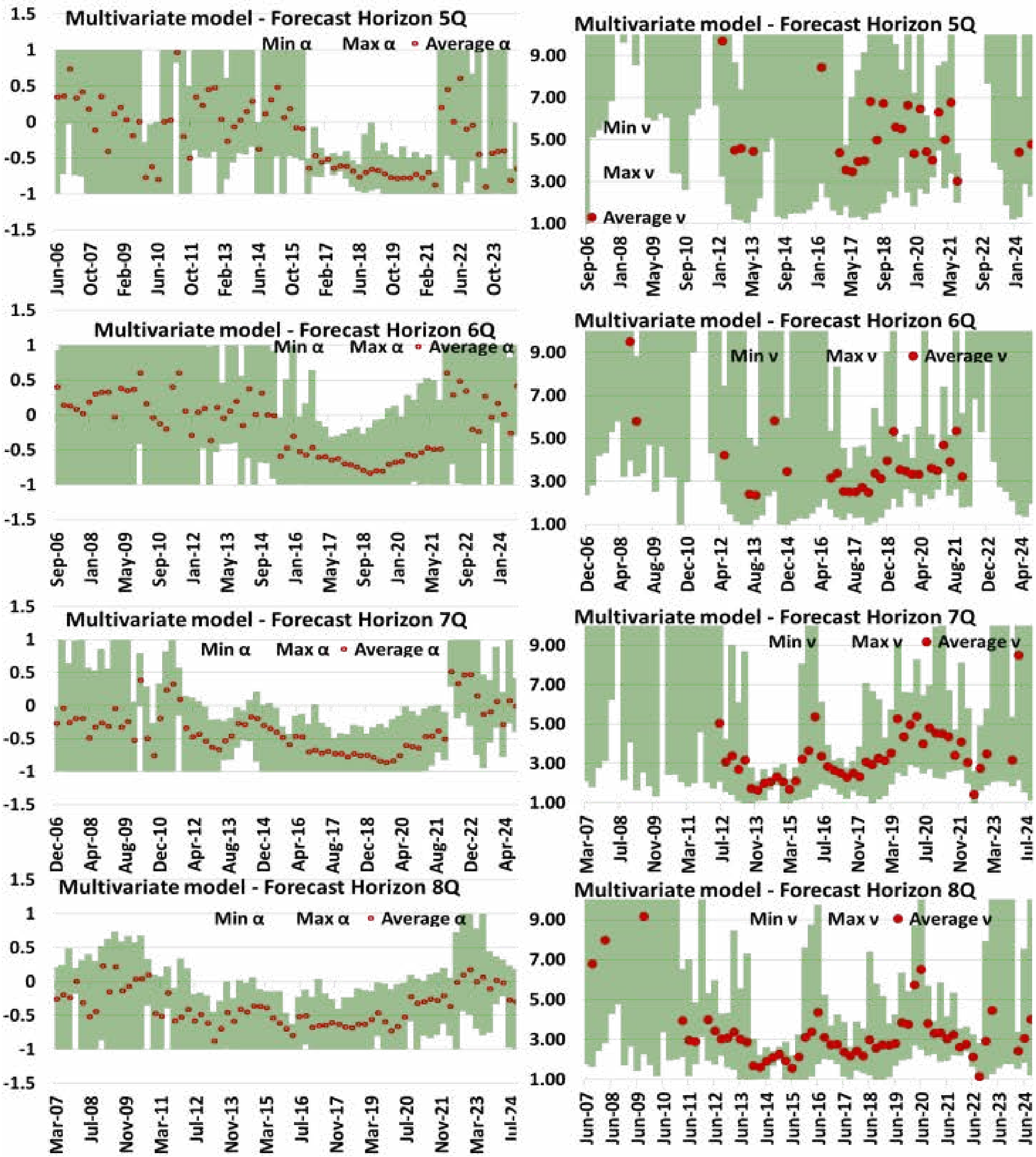


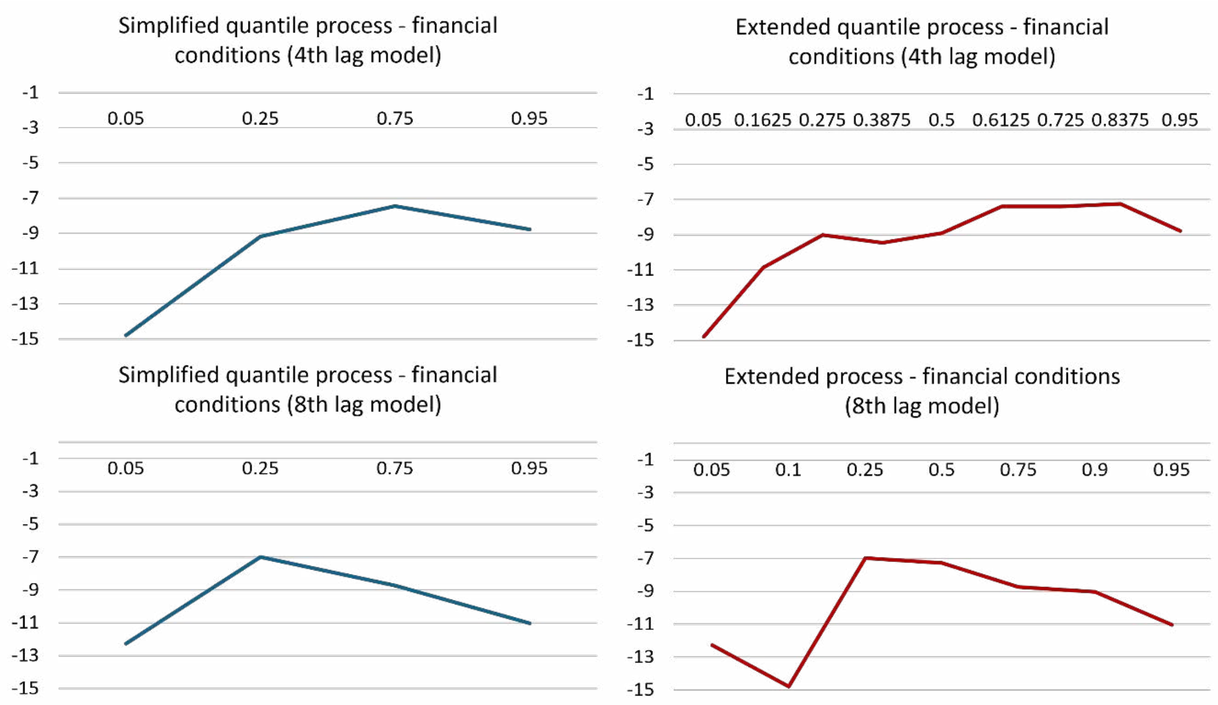
Figure A4: Continuation



Note: Min–max range (shaded) and mean (dots) of the Skewed-T parameters α (left) and ν (right), across all countries and forecast horizons. The evolution of α highlights left-tail fattening during crises, while movements in ν reflect changing kurtosis (tail thickness) over time.

Source: Author's processing

Figure A5: Quantile coefficient process for financial conditions (simple versus extended)



Notes: The figure compares financial conditions coefficients across quantiles for 4 and 8-lag models, using simplified (four quantiles) and extended specifications. The extended grid introduces instability and non -monotonicity. This supports the choice of four well-positioned quantiles for skewed-t approximation.

Source: Authors' processing

Table A1: Stationarity tests for Country-Level Indexes of Financial Stress

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–2.96***	–2.40***	–5.82***
Breitung t-stat		–5.50***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–6.82***	–5.09***	
ADF - Fisher Chi-square	91.03***	–63.94***	59.18***
PP - Fisher Chi-square	83.09***	54.13***	54.52***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.
Source: Authors' calculations, European Central Bank database

Table A2: Stationarity tests for real GDP deviations from potential

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	−4.04**	−3.59***	−9.04***
Breitung t-stat		−6.81***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	−8.23***	−6.86***	
ADF - Fisher Chi-square	122.26***	−93.71***	200.47***
PP - Fisher Chi-square	93.30***	73.97***	175.46***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.

Source: Authors' calculations, AMECO database

Table A3: Stationarity tests for Economic Sentiment Indicator

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	−0.77	0.08	−6.04***
Breitung t-stat		−4.12***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	−3.19***	−1.78**	
ADF - Fisher Chi-square	27.05***	16.57*	50.73***
PP - Fisher Chi-square	28.83***	18.32**	53.01***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.

Source: Authors' calculations, Eurostat database

Table A4: Stationarity tests for Real Interest Rate Gap

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–2.70***	–1.70**	–11.50***
Breitung t-stat		–3.17***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–9.45***	–8.47***	
ADF - Fisher Chi-square	100.26***	82.18***	160.69***
PP - Fisher Chi-square	44.22***	28.85***	72.18***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.

Source: Authors' calculations, Eurostat database

Table A5: Stationarity tests for Real Exchange Rate Gap

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–7.26***	–7.30***	–10.19***
Breitung t-stat		–4.34***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–8.28***	–7.37***	
ADF - Fisher Chi-square	87.95***	72.36***	135.79***
PP - Fisher Chi-square	45.45***	31.04***	73.94***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.

Source: Authors' calculations, Eurostat

Table A6: Stationarity tests for Credit-to-GDP gap

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–1.57*	–1.57*	–4.51***
Breitung t-stat		–2.96***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–2.83***	–1.56*	
ADF - Fisher Chi-square	27.10***	16.64*	40.14***
PP - Fisher Chi-square	22.41**	13.91	37.18***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.
Source: Authors' calculations, ECB Data

Table A7: Stationarity tests for Current Account Balance

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–1.18	–0.50	–3.37***
Breitung t-stat		–2.50***	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–1.16	–1.03	
ADF - Fisher Chi-square	13.46	12.51	28.64***
PP - Fisher Chi-square	9.16	8.27	24.19***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.
Source: Authors' calculations, Eurostat database

Table A8: Stationarity tests for dynamics of Net International Investment Position

Method	Individual intercept	Individual intercept and trend	None
Common unit root process test			
Levin, Lin & Chu t* (common unit root process test)	–1.92	3.24	–3.83***
Breitung t-stat		–1.61*	
Individual unit root process tests			
Im, Pesaran and Shin W-stat	–0.62	–0.99	
ADF - Fisher Chi-square	10.63	12.78	28.70***
PP - Fisher Chi-square	20.45**	21.17**	39.35***

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%.

Source: Authors' calculations, Eurostat database